Multidisciplinary Approach to Civil Conflict: Political, Economic, and Social Determinants of Violence

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This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Zhamilia Klycheva as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in International Politics and Political Science with a concentration in Computational Analytics.

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Abstract

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More abundant and less severe than interstate war, civil conflict has filled the news headlines worldwide, especially with nonviolent domestic instability. To this day, no single theoretical framework can fully explain this complex phenomenon. Scholars have often focused on one domain area as a precursor of violence. While such approaches are valuable, they need to grasp the whole picture, as addressing the problem from a single-domain perspective yields weak findings.

This dissertation explores specific political, social, and economic factors that impact the onset, severity, and duration of civil conflict and the frequency of nonviolent conflict. It adopts a unified transdisciplinary approach incorporating the most robust variables based on the prior theoretical findings. It examines how each factor affects each civil conflict measure in isolation and whether the joined effects produce different results. In addition to exogenous factors, it explores endogenous conflict history effects on the current violence levels. Finally, it tests each civil conflict measure across seven regions to capture a unique geographic context. Best practice political measures include political capacity, repression, and regime type. Income equality presents an economic factor, whereas gender inequality represents a social factor in the multidisciplinary framework. Additionally, transnational effects of violence are added to observe neighbor war diffusion effects.

To answer the above questions, this dissertation leverages econometric analysis conducted across 162 countries over the 1991-2018 period. Four dependent variables, onset, severity, duration, and protest

are examined via identical model specifications. The exact models are tested across seven different geographic regions to test whether the effects differ across specific regional contexts. Probit regression is used for the limited dependent variable, the onset of civil conflict. Fixed Effect Regressions with Panel corrected Standard Errors are appropriate for the three remaining dependent variables.

Econometric results reveal a unique insight into the phenomenon of civil conflict. Conflict resolution deems the most effective before its initiation. Thus, states should prioritize preventative measures such as strengthening capacity and addressing the population's needs via non-repressive means to maintain satisfaction. Coercive methods are likely to fuel grievances and increase the chances of violence. Once the violence is in place, fewer levers exist to mitigate the severity and duration of violence. Among them, strengthening state capacity and addressing the population's demands are the most effective. While coercive methods can increase the probability of onset, they can work as a pacifying force for low-level violence. Conflict duration is more challenging to manage. States with larger populations and higher democracy levels are less likely to engage in lengthy conflicts. On the contrary, countries with larger populations and a previous history of conflicts are more likely to experience nonviolent protests.

Regional analysis reveals that different areas require tailored approaches when dealing with conflict in practice. Second, violence severity and protest frequency are past-driven processes consistent with the global model results. Third, specific regions such as Sub-Saharan Africa, Europe, and North America stand out in the findings. For instance, increasing female representation in the labor force should be a priority for Sub-Saharan Africa due to its substantial negative impact on conflict severity and duration. On the contrary, gender equality can fuel the protest frequency in Western societies.

While this dissertation did not create a novel conflict measure nor solve the world's violence, it makes an effort to bring a scientific community one step closer to better understanding it. The transdisciplinary approach helped demonstrate that scholars should consider the multi-domain

approach to understanding the complexity of the conflict. Viewing the conflict from various angles revealed policy levers useful at different stages and levels of violence. Finally, the regional analysis suggested that while general conflict theory is valuable, it needs a tailored approach for the specific geographic context.

Многогранный подход к изучению гражданской войны: политические, экономические и социальные факторы

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Гражданский конфликт, как более распространенная и менее кровопролитная форма межгосударственного конфликта, ежедневно фигурирует в сводках новостей по всему миру. На сегодняшний день ни одна теория не может полностью объяснить феномен гражданского конфликта. Большинство исследований на эту тему выбирают одну конкретную предметную область и фокусируются на изучении конфликта через призму этой области. Несмотря на то, что такой подход довольно эффективен, он, по определению, не способен охватить полную картину вопроса, что и ставилось задачей этой диссертации.

Данная работа исследует конкретные политические, социальные и экономические факторы, влияющие на начало, степень жестокости и продолжительность гражданских конфликтов, а также на частоту ненасильственных событий, таких как протесты. В основе диссертации лежит единый междисциплинарный подход, включающий в себя факторы, выявленные в предыдущих исследованиях как самые важные и определяющие. В данной работе исследуется то как на гражданский конфликт влияет каждый фактор по отдельности, а также совокупный эффект всех факторов. Помимо экзогенных факторов, в работе исследуется также эндогенное влияние истории конфликта на текущий уровень конфликта. Для выявления потенциальных географических различий, каждая мера гражданского конфликта рассматривается в семи географических регионах мира. Политические факторы включают в себя политический потенциал, уровень репрессии и тип политического режима. Одним из главных экономических факторов, согласно литературе, является степень равномерности распределения доходов среди населения, тогда как гендерное неравенство является

социальным фактором в междисциплинарной структуре. Кроме того, добавлены транснациональные эффекты конфликта для наблюдения эффекта распространения войны с соседями.

Чтобы ответить на вышеуказанные вопросы, в данной диссертации используется эконометрический анализ, проведенный с участием 162 стран мира в период с 1991 по 2018 годы. В анализе используются четыре зависимые переменные: начало, степень кровопролитности, продолжительность гражданского конфликта, а также частота протестов.

Для изучения каждой из мер конфликта используются идентичные модели. Чтобы тестировать результаты в конкретных региональных контекстах, те же модели тестируются в семи различных географических регионах. Пробит-регрессия используется для ограниченной зависимой переменной, начала гражданского конфликта. Регрессии с фиксированным эффектом и стандартными ошибками, скорректированными панелью, подходят для трех оставшихся зависимых переменных.

Эконометрический анализ выявил уникальные черты гражданского конфликта. Разрешение конфликта считается наиболее эффективным до его возникновения. Таким образом, государства должны уделять приоритетное внимание превентивным мерам, таким как укрепление потенциала и удовлетворение потребностей населения нерепрессивными средствами для поддержания удовлетворения населения. Принудительные методы, вероятно, разожгут недовольство и увеличат вероятность насилия. Как только появляются искры конфликта остается меньше рычагов для смягчения его степени тяжести и продолжительности. Среди них наиболее эффективными являются укрепление государственного потенциала и удовлетворение потребностей населения. Хотя методы принуждения могут увеличить вероятность начала конфликта, они могут работать как усмиряющая сила для снижения

частоты мирных протестов. Продолжительность конфликта сложнее контролировать. Государства с большим населением и более высоким уровнем демократии менее склонны к затяжным конфликтам. Напротив, страны с большим населением и предыдущей историей конфликтов с большей вероятностью испытают ненасильственные протесты.

Региональный анализ показывает, что различные географические области требуют индивидуального подхода при разрешении конфликтов на практике. Во-вторых, серьезность насилия и частота протестов — это процессы, заметно связанные с прошлым, что согласуется с результатами глобальной модели. В-третьих, в результатах выделяются конкретные регионы, такие как Африка к югу от Сахары, Европа и Северная Америка. Например, увеличение представленности женщин в рабочей силе должно быть приоритетом для стран Африки к югу от Сахары из-за его существенного негативного воздействия на кровопролитность и продолжительность конфликта. Напротив, гендерное равенство может увеличить частоту протестов в западных обществах.

Даже если данная диссертация не создала новую меру измерения конфликта и не решила проблемы гражданской войны, она продвинула научное сообщество на крошечный шаг вперед в понимании войны. Трансдисциплинарный подход помог продемонстрировать, что ученые должны рассматривать многодоменные подходы к пониманию сложности конфликта. Рассмотрение конфликта с разных точек зрения выявило политические рычаги, полезные на разных стадиях и уровнях конфликта. Наконец, региональный анализ показал, что, несмотря на важность общей теории конфликта, она нуждается в адаптированном подходе к конкретному географическому контексту.

Dedication

I want to dedicate this work to my beloved parents, Baktybek and Dinara, who gave me everything and more to achieve what I have. You are my champions, my guiding lights, and my pride.

To my sister Azhar, for being the best big sister who always got my back and supported me throughout this journey.

To my brother Ulukbek and sister Aida for believing in me and always being there for me.

To the rest of my family, Aidai, Chyngyz, and my nieces, Nazgul and Dariya, for your patience and advice and for always waiting for me at home.

To my grandmas, Tatyi and Zulaika, for raising such amazing parents and for your sincere love.

Finally, in the loving memory of my grandfather, Sharip Klychev, who never witnessed this moment in person but lived through it in my heart.

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I want to thank the Division of Politics and Economics and all of my CGU professors and staff for your continuous support and patience throughout these years.

I want to pass my deep gratitude to my NH host family, Reta, Andy, Lilith, Anna, and Muzzy, for their open hearts and doors throughout all these years.

My Claremont parents, Greg and Barbara, for becoming my family when I needed it the most.

All my other friends and family, for your comfort during the most challenging times.

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Chapter I. Introduction

It may be true that people do not fully engage in any problem until it directly touches their lives. Among thousands of reports about global instabilities, it gets easy to feel desensitized toward this subject. Ongoing female rights protests in Iran after Mahsa Amini's death, a recent coup attempt in Peru, Taliban violence in Afghanistan, and wars in Ethiopia and Yemen, among many others, are only a tiny share of intrastate conflicts the world is experiencing today. Although such conflicts affect millions of lives daily, only a few dedicate their time to figuring out why these events happen and how they can be prevented. During my six-hour Ph.D. qualifying exam, my home country Kyrgyzstan had an attempted coup, resulting in the transition of power. This became a very personal reason and motivation to study civil conflict.

Background

Over the last decade, the world has witnessed a significant increase in data availability. With the data surge, the complexity of human behaviors can be better captured using a wide range of factors. One of the areas of interest in human behavior complexity is the study of conflict. Conflict can be considered a 'wicked problem' as it does not have a straightforward solution due to the divergent values of different stakeholders involved (Camillus 2008). It is a complex phenomenon producing consequences that require stabilization and reconstruction operations long after the conflict is over (Abdollahian, Baranick, et al. 2009). Therefore, conflict is one of the world's most difficult challenges today.

Between 1960 and 2006, 20% of nations experienced at least ten years of civil war (Blattman and Miguel, 2010). The number of civil wars in the last half a century exceeded any interstate wars, highlighting the relevance of this topic. The number of severe conflict incidents (involving at least 1000 battle-related deaths) is significantly smaller than the number of less severe violence incidents. It has consistently decreased since the early 1990s (Blattman et al. 2010). On the other hand, the number of low-level violent events, such as nonviolent demonstrations, has roughly doubled between 2011 and 2018, as shown in the graph below (Banks et al. 2021). As seen from the graph, nonviolent events demonstrate slightly different behavior. Thus, the two should be differentiated and examined separately for tailored policymaking.

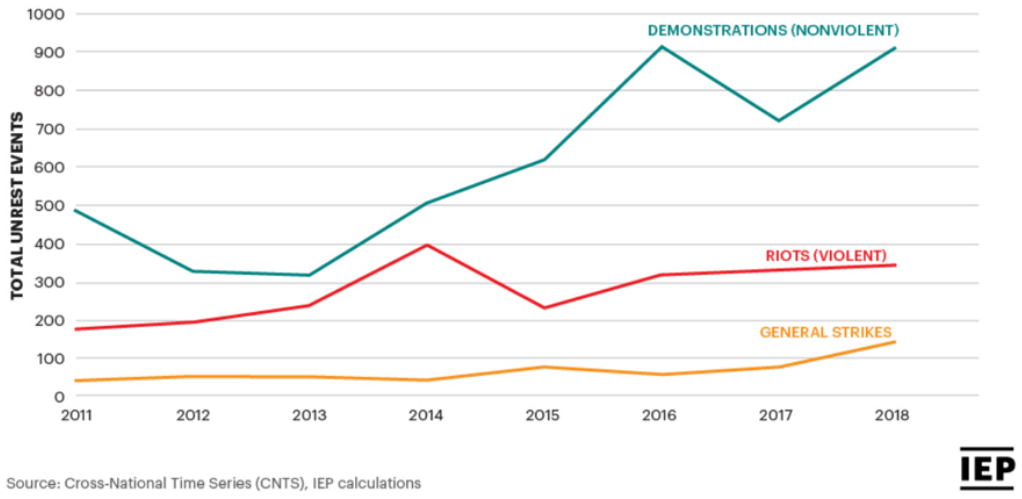


Figure 1: Global Trends in Civil Unrest, 2011- 2018

One of the critical questions scholars asked was why nonviolent events occur more frequently than violent events. While the previous literature (described in greater detail in the next chapter) has highlighted multiple paths of discovering the potential preconditions of civil violence, scholars have primarily focused on one set of factors at a time that served as precursors of civil violence. Such major factors include grievance-based socio-political conditions (Gurr 1970; 1997), economically motivated preconditions of violence or greed-based literature (Collier & Hoeffler, 1998, 2004; Fearon & Laitin,

2003), and diffusion of civil war across the borders (Gleditsch, 2002a, Gleditsch, 2007, Gleditsch et al. 2008, Sambanis and Hegre 2006). However, instead of looking at these factors separately, synthesizing and augmenting them would provide a more holistic explanation of the complex conflict behavior. This can be done by fusing multiple fields into a multi-lens framework.

Motivation

Tackling the same issue from different domain perspectives, such as political, social, economic, demographic, and technological, provides distinct solutions to the problem with weak and contradictory results. An economist can provide an economic-led solution to civil violence, most likely involving resources, labor, and capital. Demographers would probably blame youth bulge concentration on increased violence (Urdal 2006). Political scientists depending on a school of thought, would likely use structural theories of war and find power and dissatisfaction as the precursors of conflict (Organski and Kugler 1980, Tammen et al. 2000, among others). Which method should one use to develop the most consistent model and provide a comprehensive solution to the problem at a viable cost?

Previous literature has attempted to unify the existing theoretical and empirical findings into a standard set of preconditions of war (Bremer 1992, Sambanis and Hegre 2006). Similarly, this dissertation attempts to show that no single-domain approach is right or wrong. However, the most potent approach lies in integrating multiple domains or going 'broader' and using a transdisciplinary framework (Abdollahian 2021). Such a method implies not only having a political scientist in the team but an economist, sociologist, technology expert, and demographer to integrate their knowledge and

experience and synthesize the ideas in a powerful, augmented way. After all, shared knowledge is power.

Purpose of Study

Inspired by prior civil war literature, this dissertation aims to determine specific exogenous political, social, and economic factors that impact the onset, severity, and duration of civil violence and the frequency of protests. Differentiating between the measures of civil conflict will capture conflict from multiple angles and distinguish between violent and nonviolent dissent. In addition to the exogenous factors, this dissertation will test whether endogenous factors impact civil violence alone and how the effects change in the presence of the specific exogenous factors.

Measures of Civil Conflict

Most civil war studies focus on the highest violence resulting in direct fatalities. As seen above, the more severe the violence, the less frequent it is. Since less extreme events account for most intrastate instability, studying it is especially important. Scholars have used three main ways of looking at civil conflict: the onset of violence, duration, and severity. This dissertation will focus on all three measures to capture the phenomenon's complexity and, additionally, will examine nonviolent conflict, namely protest. Figure X below summarizes the four civil conflict measures. The left side of the figure outlines the measures of violent civil conflict, namely onset, severity, and duration. The right side shows nonviolent conflict measures, namely protest frequency.

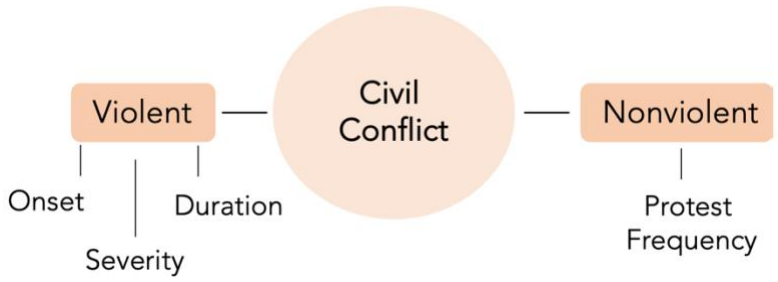


Figure 2: Measures of Civil Conflict

Overview of Methodology

This dissertation will use a transdisciplinary framework to examine the interplay of political, economic, social, and neighbor spillover exogenous factors that potentially impact civil conflict. Additionally, it will examine endogenous prior conflict's impact on the current one. Figure 3 below summarizes these factors. The left side outlines exogenous factors, and the right shows endogenous ones. Political factors include state capacity, repression, and regime type. Economic and social factors are measured by inequality. Diffusion implies cross-border violence spillover. The endogenous factor represents prior conflict measured by the lag of each DV. Additionally, a standard set of best practice controls derived from the literature is included in the modeling. Regression analyses are further used to analyze the dependent variables, namely the onset, severity, duration, and protest.

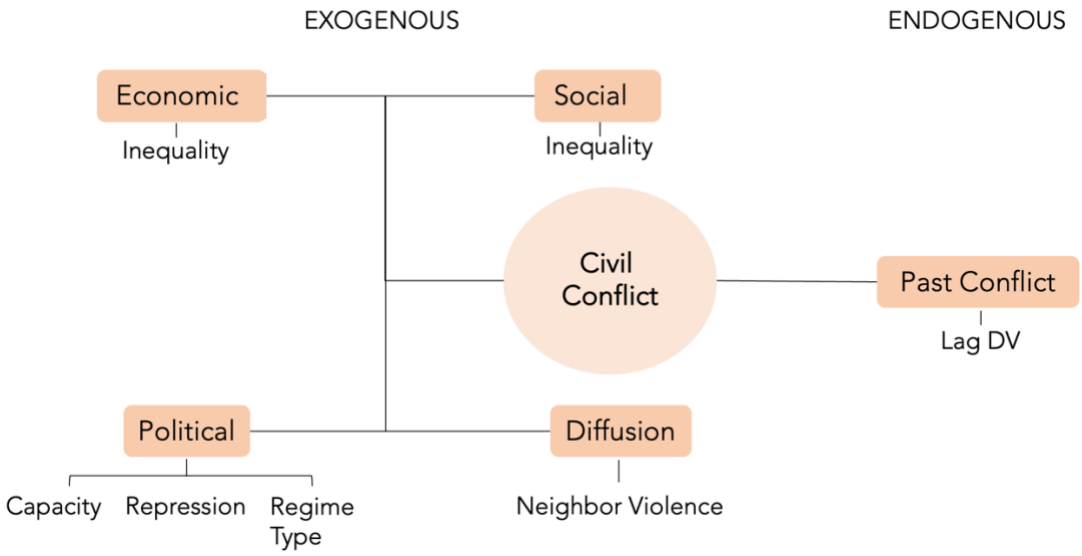


Figure 3: Methodology

Scope of Study

This dissertation will conduct a country-level global analysis of 162 countries over the 1991- 2018 time period. Additionally, the exact model specifications are tested in 7 different geographical regions to see whether the main arguments hold or region-specific effects exist.

Significance of Study

While this dissertation adds to a vast civil war literature, the main contribution is the robust multi-disciplinary framework of best practice political, social, economic, and technological variables from the prior literature. Moreover, the comprehensive measure of civil conflict allows for a granular outlook of the complex problem. Examining endogenous and exogenous factors impacting civil conflict enables one to isolate the two processes and see whether one is significant in the presence of

the other. Additionally, regional analysis tests if these factors hold across different samples and whether specific geographic differences exist to tailor policymaking.

Limitations

One of the most common limitations relevant to this dissertation is the measure of civil conflict. This research adopts low criteria to define civil conflict onset and does not restrict the number of casualties for it to be considered an onset.[1] Additionally, the limited sample size through 2018 is attributed to the limitations of the few independent variables at the moment of the research initiation. Finally, while simple regression analysis has proven robust and parsimonious, it has limitations. Further research can utilize more sophisticated computational tools.

Structure of the Dissertation

This dissertation follows a standard research structure, first introducing the phenomenon of interest and highlighting its importance. Then it will review the relevant literature and provide the motivations behind each variable's origin and measurement. Further, it will detail the Methodology by listing the research questions, hypotheses, and tools to examine the subject of interest. It will then provide a detailed overview of the data and its sources. Next, Exploratory Data Analysis (EDA) will provide helpful visualization and a complete description of the underlying data to be used in the analysis. Full model specifications are provided before model results. The Results section summarizes global model outcomes for onset, severity, duration, and protest. The same models are replicated in the regional

[1] The severity of conflict already captures the number of casualties; therefore, the onset measures any civil conflict regardless of the number of fatalities for a greater sample variation.

samples. Finally, the dissertation will conclude by revisiting the hypotheses, providing policy implications, and reflecting on what went right or wrong.

Chapter II. Literature Review

This chapter will conduct an overview of the relevant civil war literature that serves as a foundation for the research design proposed in the Methodology chapter to identify the structural determinants of civil conflict. Firstly, it will explain the concept of civil war and its specification. Secondly, it will determine the most robust variables used to study the phenomenon of interest. Lastly, it will point out the problems with the existing empirical approaches in the field and potential ways to overcome them.

Despite the variety of studies in the civil war literature, a consensus has yet to be reached on the exact precursors of civil conflict. Authors in the past have mainly adopted inductive reasoning, deriving the most robust structural predictors of civil war (Sambanis 2004, 2006). Among those, grievance-based and greed-based factors appear among the most prominent ones in the literature.

Intrastate violence is a separate category of conflict distinct from interstate violence. It branches off in the International Studies literature and has different determinants. According to Singer and Small (1994), civil war is an event that occurs within a state's borders. It involves government and non-state actors, where both warring sides have to inflict harm on one another. Authors in the past have proposed a high threshold of 1,000 battle-related deaths for it to be considered a full-scale 'civil war' (Singer and Small Correlates of War Project, 1994). This measure has been further refined by Sambanis (2004) by accounting for population size and decreasing the number of deaths, thus making the criteria less restrictive. This dissertation will consider all instances of civil violence as long as they involve at least one battle-related death, allowing for more variation in the sample. Further measures of civil violence will help control for its severity, explained in greater detail in the Methodology chapter.

Civil conflict has been primarily measured from three angles: its onset, duration, and severity. Onset indicates whether violence began and represents one of the most common ways to measure intrastate violence (Collier & Hoeffler, 2004; Fearon & Laitin, 2003; Gleditsch et al., 2001). Duration measures a length of a given conflict. Collier, Hoeffler, and Soderbom (2001) find that the determinants of civil conflict duration differ from the onset's, necessitating separate analyses. The smaller portion of the literature has focused on the severity of the conflict. However, conflicts vary from minor violence with few casualties to full-scale wars carrying away thousands, if not millions, of lives. Lacina (2006) warns that knowing why the war starts does not mean knowing when it will be most severe.

While measuring civil violence from three different angles, it is essential to differentiate between the types of violence. Regan and Norton (2005) examined three measures of civil conflict: protest, rebellion, and civil war. They found that the same set of predictors shows considerable differences in results for all three dependent variables, especially for the lowest form of violence - protests. Thus, examining low-level violence in addition to the more severe violence cases allows for nuanced policymaking.

Civil war literature has primarily adopted a correlational approach, identifying structural conditions that make states more or less prone to experiencing civil conflict. One branch of the civil war literature follows grievance-based motivations for violence. Its roots date back to Ted Gurr's relative deprivation theory, which explains this concept as a perceived difference between expectations and capabilities (Gurr 1970). Grievance-based literature rests on the rationale that conditions such as government repression, discrimination, and income inequality, among others, can potentially create grievances or dissatisfaction among individuals or groups of individuals, 'galvanizing collective action' and creating a favoring environment for potential civil violence (Florea, 2017; Collier and Hoeffler, 2004; Collier, Hoeffler, & Rohner, 2009; Fearon and Laitin, 2003).

The second sizeable correlational framework is greed-based, focusing on rebels' opportunity costs for participating in a conflict or economically motivated grievances. These factors include conditions that favor insurgency or make it more feasible. For instance, the state's weakness, large populations, past dependence on war, regime type, and low economic development have a robust predictive capacity toward civil war (Collier and Hoeffler 1998, 2004; Fearon and Laitin 2003).

As mentioned above, within the 'greed-based' framework in the civil war literature, past dependence on war is one of the factors potentially favoring new insurgence. States with a prior war history have a higher risk of war reoccurrence. Once initiated, violence may "follow a path-dependent process" (Collier & Sambanis 2001). One way to account for the prior conflict is to include a lag of the dependent variable (Cederman & Girardin 2007). While concerns exist about the validity of lagged DV (LDV) inclusion, failure to include the LDV may lead to serious omitted variable bias. Wilkins (2017) finds that including LDV produces the best estimates of the effects of the independent variables on the dependent variable of interest.

Civil violence occurs within a state's physical boundaries, making the government one of its key players. As mentioned above, the government's weakness was considered as one of the factors potentially favoring insurgency fitting within the 'greed-based' framework in the civil war literature (Florea, 2017). Capable governments can successfully implement their political, social, and economic agenda, contributing to the population's well-being and potentially changing the direction of conflict. Scholars have previously measured governments' economic penetration within societies via taxation (Lotz and Morse 1967, Bahl 1971). Organski and Kugler (1980) were the first to realize that these variables indirectly measure state political capacity. The connection between government revenues and political performance can be traced via the state's economic endowment and prior commitments to the public and private sectors (Organski and Kugler 1980). Thus, political capacity can be measured

as the difference between the resources the governments can extract and the resources they are willing to extract (Benson and Kugler 1998).

The measures were later refined by Kugler and Arbetman (1997) and Tammen et al. (2012) into Relative Political Capacity (Performance of Nations, 2012). Feng (2006) demonstrates that state political capacity increases when political campaigns prioritize it; the opposite is true when economic reforms are the driving force. On an intrastate level, only Benson and Kugler (1998) have applied state political capacity and found that relative political extraction significantly impacts the severity of civil violence. One of the latest state capacity operationalizations incorporates life expectancy. It is discussed later in the Data section of Methodology (Fisunoglu et al., 2020).

Regime type is another essential factor within the 'greed-based' framework for studying civil conflict, potentially encouraging or discouraging rebel behavior. Benson and Kugler (1998) find that state capacity has a more substantial effect on conflict in the presence of democracy. Hegre (2001) finds that semi-democracies are the least stable regime type. The risk of conflict significantly declines for highly democratic or autocratic states, showing the nonlinear nature of the relationship (Gleditsch and Ruggeri 2010). Yet, democratic states are more stable in the long run than autocratic ones (Hegre 2001).

While political capacity is essential in mitigating civil conflict, it does not directly measure state coercion that can directly impact violence. State repression appears within the "grievance-based" literature and can potentially increase the likelihood of conflict occurrence (Young, 2012). Political repression measures a state's violation of fundamental human rights, such as physical integrity, and implies restrictions on political activity imposed by the state (Gibney et al., 2020). In early studies, Gurr and Moore (1997) claim that political repression positively affects rebellion via mobilization.

Moreover, Hegre (2001) finds that repression is associated with increased intrastate violence, excluding cases of severe repression. More substantial evidence suggests that repression can exacerbate intrastate conflict (Lichback, 1987; Tarrow, 1994; Gurr and Moore, 1997). In more recent studies, the literature finds repression's non-monotonic effect on civil violence. Regan and Norton (2005) claim that political repression negatively impacts nonviolent intrastate events but has significant and positive effects on the onset of the rebellion. This suggests that political repression might positively contribute to the escalation of civil violence. At the early stages of mobilization, when protesters have demands but no coherently formed groups, state repression can potentially pacify such movements. However, at later stages of mobilization, when demanders have developed solid groups of opposition and can back each other, government repression increases the potential violence onset.

Among the economically motivated grievances, Fearon and Laitin (2003) find that rising income inequality is associated with the increase in civil violence, confirming Gurr's economic discrimination motivations towards warfare. Additionally, Cederman et al. (2011) find that in highly unequal societies, individuals fight more frequently than in those societies where wealth is more evenly distributed within the population. While economic inequality has a firm place in the civil war literature, gender inequality received far less attention (Fearon and Laitin 2003, Collier and Hoeffler 2004, Hegre and Sambanis 2006).

Few scholars have linked gender inequality both directly and indirectly to armed violence. Gender equality's indirect effect on conflict are the norms enhancing violence. Societies with higher gender inequality are presumably more patriarchal and male-dominated, which would normalize violence and warlike toughness, potentially contributing to the violence (Hudson et al., 2008– 2009). In these cases, violence would be legalized to resolve conflict (Caprioli 2005, p. 163). Gender inequality's direct effect implies males' mobilization and aggression as an immediate positive effect on war (Fukuyama 1998).

From an economic standpoint, Regan and Paskeviciute (2003) consider limiting women's access to the labor market as decreasing the society's capacity, as fewer members have the skills and resources to affect developments.

Collier and Hoeffler (2004) find that the 'greed,' or economic opportunities that favor the rebellion, such as primary commodity exports, economic development, and growth, provide more explanatory power than ethnicity-based factors. They find that countries with both high levels of development and growth rate are less prone to civil conflict. Fearon and Laitin (2003) contribute by finding that conditions favoring the insurgency, such as large populations are much stronger predictors of violence than ethnicity-based variables that remain popular in the literature (Collier and Hoeffler 1998, 2004; Hegre 2001, Hegre and Sambanis 2006, Sambanis 2004, Lemke and Crabtree 2018). They find primary commodity exports as a secondary factor that potentially increases the likelihood of internal conflict (Collier & Hoeffler, 2004)

Though civil war physically occurs within the state borders, the prior literature has revealed potential neighbor violence diffusion across the border. This body of literature challenges the 'closed polity' concept and introduces the 'bad' neighbor concept (Weiner 1996). It finds significant evidence of adjacent conflict diffusion within state boundaries (Gleditsch, 2002a, Gleditsch, 2007, Gleditsch et al., 2008, Sambanis and Hegre, 2006). Gleditsch and Rivera (2015) find strong neighbor spillover effects but little evidence for global violence diffusion.

Increasing connectivity and technological advancement have changed the current warfare landscape. Abdollahian (2021) described technology as an "enabler" that allows one to reconfigure strategies and accelerate modern 'hybrid' warfare. Accounting for these factors has become essential in shaping policymaking. Barbieri and Reuveny (2005) found significant effects of internet use on civil war onset,

specifically for developing countries. Controlling for this feature is essential when studying civil conflict.

Prior literature has adopted a correlational approach to studying civil conflict. The literature was divided into two main frameworks: greed-based and grievance-based factors influencing civil conflict. Previous war history, state capacity, regime type, and population, among other economically motivating factors such as development, growth, and commodity exports, fall under the 'greed' framework. State repression and inequality measures can fall under the 'grievance' umbrella. Other factors, such as neighbor violence diffusion and technology use, have also been significant in predicting civil conflict. While no consensus exists in the literature, this dissertation will leverage these empirical findings and propose a multi-lens approach to studying low and high-level violence. The next chapter will lay out a proposed research design that augments the discussed literature into a single framework for analyzing civil violence.

Chapter III. Methodology

This chapter proposes a transdisciplinary research design to analyze the intrastate conflict. First, it outlines the research questions. Second, it summarizes the main hypotheses and highlights suitable modeling techniques to answer those questions. Third, it fully describes the underlying data used in the analysis, including the sample size, variable measurement, and data sources.

Research Questions

This dissertation aims to answer what specific political, economic, and social factors impact the onset, severity, and duration of civil conflict. Moreover, it investigates whether the same factors hold for low-level civil violence, namely protests. Below are the research questions and subsequent hypotheses addressed in this work.

a) Does the endogenous prior history of violence impact the current conflict?
    a. If so, how much does past conflict alone determine future conflict?
b) What role do specific exogenous political, economic, and social factors have on civil conflict?
    a. How do these specific effects hold when viewed separately?
    b. What are the combined effects of these factors when viewed in the context of standard conflict controls?
    c. How do specific exogenous factors influence conflict in the presence of endogenous past conflict histories?
c) Do the same factors hold for different levels of conflict onset, severity, duration, and protest as different dependent variables?
d) Given the above, how do these factors change across different geographic regions?

To answer the research questions above, the following core hypotheses are proposed.

Hypotheses

H1: Prior history of violence positively impacts the current level of conflict onset, severity, duration, and protest.

H2: Political Capacity has a negative impact on the onset, severity, and duration of the conflict.

H3: Political Repression has a positive impact on conflict onset and severity but a negative impact on protest frequency.

H4: Democracy has a negative impact on conflict onset, duration, and severity but a positive effect on protest frequency.

H5: Income and gender equality have a negative impact on conflict onset and severity.

H6: Adjacent conflict positively impacts conflict onset, severity, and protest frequency but not the duration.

This dissertation will examine both violent and nonviolent civil conflict to test the above hypotheses. Four dependent variables are examined, namely onset, severity, and duration of violent conflict, and the frequency of nonviolent protests. Each dependent variable has identical empirical model specifications with the only exception of the lags of DVs, unique to each model. This research design proposes Probit regression for the limited dependent variable, namely the onset, and Fixed Effects OLS regressions for the remaining continuous variables: severity, duration, and protest. A standard 95% significance level will be used as a cutoff point for hypothesis testing for more restrictive results. Later, the results section will describe the econometric specifications and approaches for each dependent variable in greater detail.

Data

The data section below will provide a comprehensive summary of every variable used in the modeling part of the dissertation. First, it will describe each one of the dependent variables. Then it will specify

theoretical and control variables. The primary sources of data are UCDP, TransResearch Consortium, Polity Project, World Bank, and Harvard Dataverse, among others.

Sample Overview

The dataset follows a panel format of 162 countries measured between 1991 and 2018 (28 years). The start year is 1991 to capture the Former Soviet Union states, which gained their independence in 1991. The end year is 2018 due to the data available at the time of the research initiation. The total sample size is 4536 observations.[2] The unit of analysis is country/ year.

Dependent Variables

The Onset of Civil Conflict

The first measure of civil conflict is the onset of violence. The onset of civil conflict indicates the initiation of new violence in a given year and country. It is derived from the UCDP Georeferenced Event Dataset, V22.1 (Gleditsch et al., 2002; Shawn et al., 2022). Events reported in the current dataset are categorized as incidences of armed force by an 'organized actor against another organized actor' that results in at least one death (Pettersson, 2022). Such events are not necessarily targeted against the government. If there is at least one new incidence of violence in a given year, the variable takes a value of 1. Otherwise, it is coded as 0 for no conflict onset in that particular year and country. Each instance of new conflict onset is differentiated based on the 'unique identification code for each conflict in the dataset' (Pettersson, 2022). As long as the conflict reported in the dataset has a unique "conflict id" identifier, it is counted as a separate onset[3].

[2] See Figure i in the Appendix for the full list of countries by region.
[3] This is done to avoid double counting of the same conflict that may reoccur in consecutive years.

The Severity of Civil Conflict

Traditionally, the severity of civil conflict has been measured as the number of casualties resulting from a direct incidence of violence. Taken from the same UCDP dataset, fatalities are a direct outcome of events involving arms between two organized groups fighting one another (Gleditsch et al., 2002; Shawn et al., 2022). The fatalities variable undergoes logarithmic transformation due to the skewness in the data distribution. The log of fatalities ranges between 0 and 14.079.

The Duration of Civil Conflict

As the name suggests, the duration of conflict measures the length of each unique civil conflict.[4] It is calculated as the total number of days a given country engaged in civil conflict in a given year. The number of days can exceed 365 as multiple conflicts may co-occur.[5] This variable is derived from the same UCDP dataset (V22.1) as the two variables described above. It undergoes a logarithmic transformation for normalization purposes.[6] The log value of conflict duration ranges from 0 to 10.2 in the given sample.

The Frequency of Nonviolent Conflict

The same factors impacting severe violence may not hold for mild conflict incidents. For this purpose, a low-severity type of conflict, namely protest, is used in this dissertation. A protest event is described as a gathering involving at least 50 people to make a demand to the government. This action is a "homegrown" demand targeted at a state or state policy (Clark, Regan, 2015). Though some previous literature has operationalized protest as a limited dependent variable (Dahlum and Wig, 2019), this

[4] Each unique conflict is differentiated based on a unique conflict identifier to avoid double counting.
[5] This variable is not capped at 365, taking into consideration multiple conflicts occurring that are counted separately
[6] The original value of duration ranges from 0 to 26,914 days, with a positively skewed distribution. Logarithmic transformation serves as a normalizing measure to smooth the variable behavior commonly applied in regression analyses.

dissertation will measure Protest as a frequency measure, measured as the number of protest events that occurred in a given country and year. The frequency measure answers a broader question of what leads to an increase or decrease in the number of protests, as opposed to a limited question of whether protests will occur. Due to the skewness in the data, logarithmic transformation is applied. Log protest ranges between 0 and 4.97 in the current sample.[7]

Theoretical Variables

As mentioned in the Literature Review chapter, it is essential to account for endogenous and exogenous factors impacting violence. A simple way to account for endogenous processes is by including a lag of the dependent variable. Prior conflict measures the history of each dependent variable; in other words, it is the endogenous process for civil conflict. It is calculated as a one-period lag of each dependent variable (onset, severity, duration, and protest). The lags have the same variable ranges as the main DVs described above.

Absolute Political Extraction (APE) is a measure of state political capacity. Like Relative Political Extraction (RPE), APE relies on tax extraction as a measure of state capacity but consists of two subcomponents: political extraction capacity and life expectancy (Fisunoglu et al. 2020).[8] Recalling from the TransResearch Consortium codebook, Relative Political Capacity (RPE) measures the government's ability to "appropriate portions of national output to advance public goals" (Kugler, Tammen 2012). The RPE calculations for both developing and developed countries, correspondingly, are shown below:

[7] Protest variable is also positively skewed and undergoes a logarithmic transformation for the same purpose as fatalities and duration.

[8] Unlike RPE, APE corrects for the punishment of states in higher stages of economic development.

Developing societies (Model 1) (rpe_agri):

$$\frac{\text{Tax}}{\text{GDP}} = \alpha + \beta_1(\text{time}) + \beta_2\left(\frac{\text{Mining}}{\text{GDP}}\right) + \beta_3\left(\frac{\text{Agriculture}}{\text{GDP}}\right) + \beta_4\left(\frac{\text{Exports}}{\text{GDP}}\right) + \beta_5(\text{OECD}) + \beta_6(\text{Inclusion Dummy}) + \varepsilon$$

Figure 4: RPE Calculation for Developing Societies

Developed societies – General Sample(Model 2) (rpe_gdp):

$$\frac{\text{Tax}}{\text{GDP}} = \alpha + \beta_1(\text{time}) + \beta_2\left(\frac{\text{Mining}}{\text{GDP}}\right) + \beta_3\left(\frac{\text{Exports}}{\text{GDP}}\right) + \beta_4(\text{GDP per capita}) + \beta_5(\text{OECD}) + \beta_6(\text{Inclusion Dummy}) + \varepsilon$$

Figure 5: RPE Calculation for Developed Societies

While the former (RPE) measures the state's extraction capability, the latter (APE) intends to measure the state's political performance via the longevity of living. Life expectancy captures the state's socio-economic conditions, access to healthcare, and the government's ability to provide these conditions. The formulas below summarize the APE calculation. Political Extraction Efficiency calculation is shown first, followed by the APE calculation below. APE takes values between 0 and 1. 0 implies the least capable, and 1 indicates the most capable state.

All societies – General Sample (Model 1) (ape1):

$$\ln\left(\frac{\text{Tax}}{\text{GDP}}\right) = \alpha + \beta_1 \ln\left(\frac{\text{Mining}}{\text{GDP}}\right) + \beta_2 \ln\left(\frac{\text{Exports}}{\text{GDP}}\right) + \beta_3 \ln\left(\frac{\text{Social Contributions}}{\text{GDP}}\right) + \beta_4 \ln(\text{GDP per capita}) + \beta_5(\text{Economically Active Population}) + \beta_6(\text{Education}) + \beta_7(\text{OECD}) + \beta_8(\text{Inclusion Dummy}) + \varepsilon$$

Figure 6: Political Extraction Efficiency Calculation

$$\text{APE} = \text{political extraction efficiency} \times \text{life expectancy}^{9}$$

Figure 7: APE Calculation

Political Repression is defined as 'violations of basic human rights to the physical integrity of a person by agents of the state' (Gibney et al., 2020).

[9] Both subcomponents are standardized between 0 and 1, applying Frontier Approach for absolute measure.

'Agents of the state' are any parties acting on behalf of a state, including police, military, death squads, political parties, and foreign personnel such as peace-keepers aiding domestic capacity (Haschke, 2019). Those 'violations' imply any physical acts of violence such as torture, beating, killing, political imprisonments, and kidnapping, among others. This categorical variable is measured on a 5-point ordinal scale, ranging from 1 to 5. The lowest repression level of 1 indicates a country under a secure rule of law without imprisonment for views. The highest value of 5 implies repression extended to the entire population, where leaders of states place no limits in pursuing their own ideological goals state' (Gibney et al., 2020).

Democracy measures regime type in a given state in a reported year. It is a categorical variable measured on an ordinal scale, ranging from 0 to 10. Zero indicates the lowest level of democracy, and ten reflects the highest (Polity5 Annual Time Series, 2020). The elements of this scale include the competitiveness of executive recruitment, the openness of executive recruitment, the constraint on the chief executive, and the competitiveness of political participation (Marshall et al., 2021). According to this scale, a mature democracy encompasses free political participation and elective executive commitment with substantial constraints on the chief executive[10]. While other sources and measurements of regime type exist, this dataset has proven to be robust in the previous literature (Hegre et al., 2001).

Income Equality is intended to measure the disparity of income distribution throughout the population. While multiple income equality measures exist, the closest proxy has been selected due to the data limitations on a global sample. This dissertation measures the total pre-tax national income share of the bottom 50% share of the population (Alvaredo et al., 2020, World Inequality Database).[11] The variable takes values between 2.96% and 29.11% in the current sample.

[10] Visit Figure ii in Appendix for a detailed Democracy measurement.
[11] The population comprises individuals above 20 years old, not households.

Gender Equality captures access to economic opportunities based on gender in a given state and year. The closest proxy available for the total sample size is women's economic participation in the labor force (World Bank Data). It is calculated as a ratio of female labor force participation to male labor force participation. This ratio shows the disparity between females' and males' economic participation [12]. The labor force is derived from the economically active population of 15 years or older. The variable value ranges from 8.73% to 109.12% in the given sample.

Adjacent Conflict is measured as a dummy variable indicating whether a contiguous state is involved in an armed intrastate conflict in a given year. The value of 1 indicates that for a given country, at least one of its contiguous neighbors was involved in a civil conflict in the reported year. Zero indicates otherwise. The data is derived from the same UCDP Georeferenced Event Dataset, V22.1, used to measure the three dependent variables: onset, severity, and duration (Gleditsch et al., 2002; Shawn et al., 2022).

Control Variables

Inspired by the literature, this section describes the best practice economic, technological, and demographic control variables that help explain the four dependent variables of interest (onset, severity, duration, and protest).

Economic Development reflects the state's level of economic development in monetary terms. It is measured as a log of GDP per capita (World Bank) to adjust for the population size of each country.[13] The log of GDP per capita variable ranges from 6.1 to 11.7 in the given sample. Based on the prior literature, economic development is one of the most important control variables, emphasizing the

[12] Due to the lack of gender inequality data on a global scale, the current measure was used as a proxy of gender inequality.
[13] GDP Per Capita, PPP (Constant 2017 International $).
Since the original value of the GDP per capita is highly positively skewed, the common logarithmic transformation is applied.

state's different development stages when measuring conflict (Collier and Hoeffler 2004). For instance, Fearon and Laitin (2003) found that ethnically or religiously diverse communities were no longer significant after controlling for economic performance.

While economic development reflects an overall economic standing, the economic growth rate reveals how far it is on its trajectory toward steady state growth. Countries with a low development level may have a high growth rate, and countries with high GDP per capita may develop at a slow rate. Those two factors contain different but complementary pieces of information, adding more context to the full model. Economic growth is measured via Log of GDP per capita growth. It takes values between -6.4 to 4.9 in the current sample.

Commodity Exports is the following control variable that reflects the country's outgoing economic activity. It is measured as exports percent share of GDP[14]. Collier and Hoeffler (2004) find primary commodity exports as a strong predictor of civil violence. The variable is provided by World Bank and ranges from 0% to 229% in the given sample.

Internet use is a technological factor in the transdisciplinary research design. It measures the population's access to technology, namely the internet. Based on past literature, internet use has a significant impact on conflict (Barbieri & Reuveny, 2005). Controlling for this variable could bring in value. Internet use is measured as the percent of the population that has access to the internet, provided by the World Bank Dataset[15]. It ranges from 0% to 100%, where 100% indicates full access to the internet by the entire population.

[14]"Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments" (World Bank WDI, 2018).

[15] Individuals using internet, % of population, World Bank

The population is the last variable representing a demographic control to account for the population size of a given country and year. This variable is commonly used in the civil war literature (Hegre and Sambanis 2006, Fearon and Laitin 2003, Collier and Hoeffler 2004, Ghatak 2013). It is measured in thousands and undergoes a logarithmic transformation as a standard way of normalizing a positively skewed distribution (World Bank).[16] The values in the current sample range between 5.3 and 14.1.

[16] Log (Population/ 1000) consistent with Fearon and Laitin 2003.

Chapter IV. Exploratory Data Analysis

Analyzing data or conducting exploratory data analysis (EDA) is essential in a quantitative research design before modeling the data. It aims to reveal the underlying structure and patterns in data, identify potential measurement errors and outliers, paint the distribution, and confirm the appropriate modeling techniques. While descriptive analysis is essential, "…a picture is worth a thousand words (San Antonio Light, 1918)." Visualizing provides a simplified, digestible way of looking at vast data. This chapter will summarize the variables introduced in the Methodology chapter, describe their structure, and identify relationships between independent and dependent variables, namely onset, severity, duration, and protest.

Descriptive Statistics

This subsection summarizes the available data by providing the number of observations, mean, standard deviation, and minimum and maximum values for variables. This dissertation performs a global country-level analysis of 162 countries within the 28-year over the 1991-2018 time period. The full sample size is 4,536 observations.

Dependent Variables

Table 1 below provides the summary statistics for each one of the dependent variables, namely the onset, severity (fatalities), duration, and protest frequency. Dependent variable data is available across the entire sample (N= 4,536). Onset is the first binary dependent variable that equals 0 or 1. The mean value of 0.2 indicates the predominance of peace across the dataset, as onsets occur only 15% of the time within the given time frame.[17]

[17] There are only 685 onsets within the full sample of 4536, resulting in roughly 85% of peace periods.

The second dependent variable is a log of fatalities that operationalizes the severity of the conflict. As seen from the table, it is highly unbalanced, with a mean of 1.6 and a substantial standard deviation of 2.8. 14.1 is the highest value of fatalities for a single year across 162 countries.[18] This outlier belongs to one of the most significant violence in the civil war history, the Rwandan genocide. To help smooth data skewness, logarithmic transformation is applied.

Variable	N	Mean	St. Dev.	Min	Max
onset	4,536	0.2	0.4	0	1
lndeaths	4,536	1.6	2.8	0.0	14.1
lnduration	4,536	0.5	1.7	0.0	10.2
lnprotest	4,536	0.9	0.9	0.0	5.0

Table 1: Dependent Variables Summary Statistics

The third dependent variable is the duration of civil violence. The log of duration has a mean of 0.5 and a standard deviation of 1.7. It ranges from 0 to 10.2. Duration's original value has a mean of 112 days. Since it accounts for multiple co-occurring conflicts and can exceed 365 days, it takes values as high as 26,914 days of concurrent conflicts per year.[19] Sierra Leone had the highest value of 26,914 in 1991, reaching the record conflict duration in the sample.

Finally, protest is the fourth dependent variable measured as the log of protests in a given year and country for normalizing purposes. Log protest has a mean and standard deviation of 0.9, ranging from 0 to 5. Protest's original value has a mean of 3 and a standard deviation of 6 across 162 countries and 28 years. The largest number of protests in the sample occurred in Kenya in 2015 (143 protests).

The subsection below will examine time series plots of each individual dependent variable.

[18] The original value of fatalities has a mean of 825.5 and a standard deviation of 19,581.5 casualties, with the highest value of 1,301,020 fatalities.

[19] The standard deviation is relatively high at 947.5, roughly eight times the average value. The data is unbalanced, with fewer prolonged conflicts contributing to the longevity of violence.

Figure 8 below shows the sum of onsets between 1991 and 2018 across the world. 1991 stands out with the most conflict onsets. These events include Soviet Union's collapse, the ongoing Gulf War in Kuwait, and the African conflicts, i.e., in Sierra Leone and Somalia. The number of new conflicts noticeably decreases in the following years, with a slight climb around the early 2000s, possibly due to the violence on Russian territory and the US invasion of Afghanistan following the 9/11 attack. Throughout the first decade of the XXI century, new conflict onsets gradually decline, slowly increasing in the mid-second decade. This may be due to the conflicts in North Africa (Libya, Yemen) and a resurgence of violence in Afghanistan. The dataset ends with a moderate level of onsets by 2018.

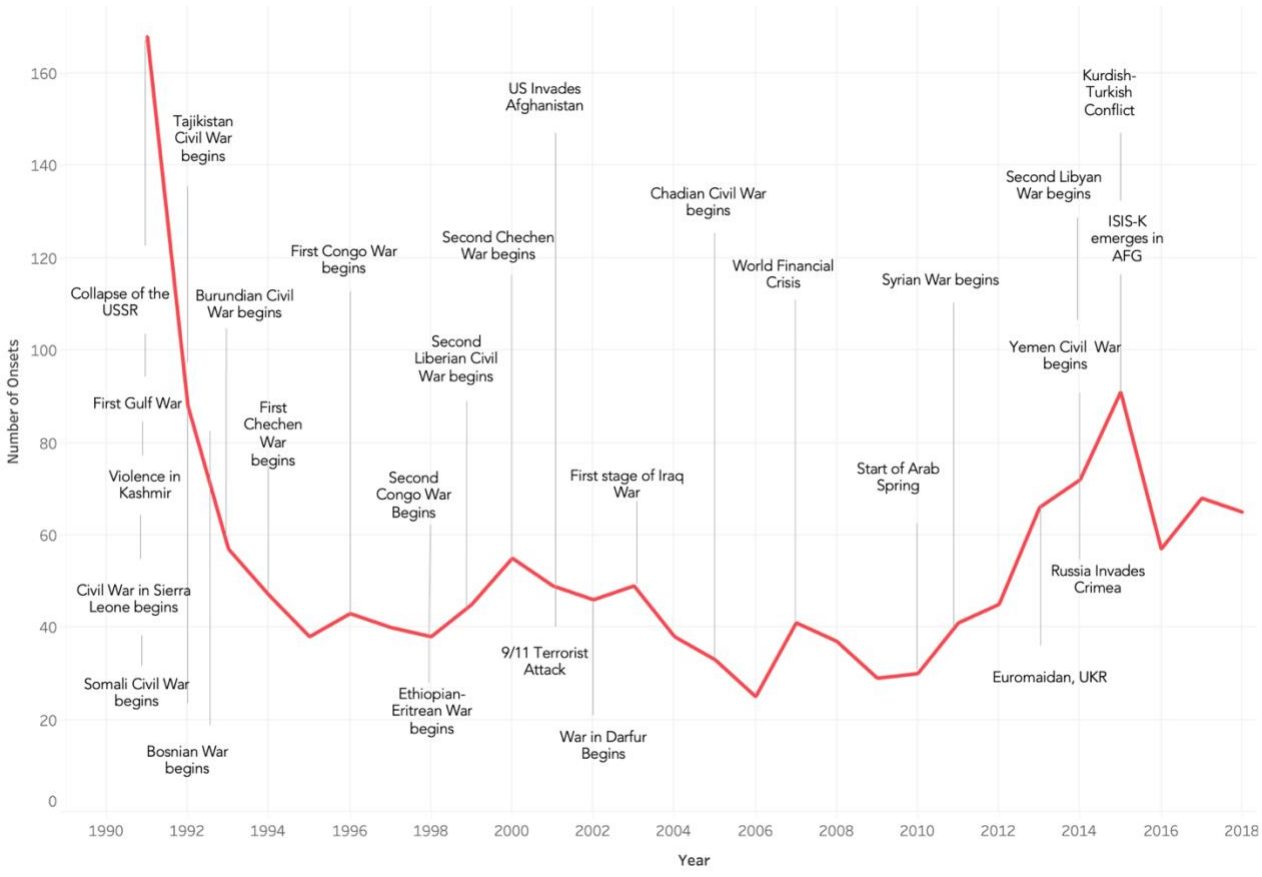


Figure 8: Sum of Onsets Over Time

Figure 9 below shows the time series plot for the total annual fatalities across 162 countries. 1994 marks the deadliest year in the world, primarily attributed to the Rwandan genocide resulting in

roughly 1 million deaths. Recalling from the onset time series plot, most new conflicts occurred in 1991, gradually decreasing and maintaining relatively consistent levels after. Fatalities time series shows a spike in casualties in 1994, immediately declining afterward and maintaining relatively constant levels. This seems intuitive as conflict-related deaths occur in the following years of violence initiation. This explains the delay between 1991 to 1994. Both onset and fatalities numbers increase towards the second half of the 2010 decade. Among these events are the Arab Spring and the Russian invasion of Ukraine.

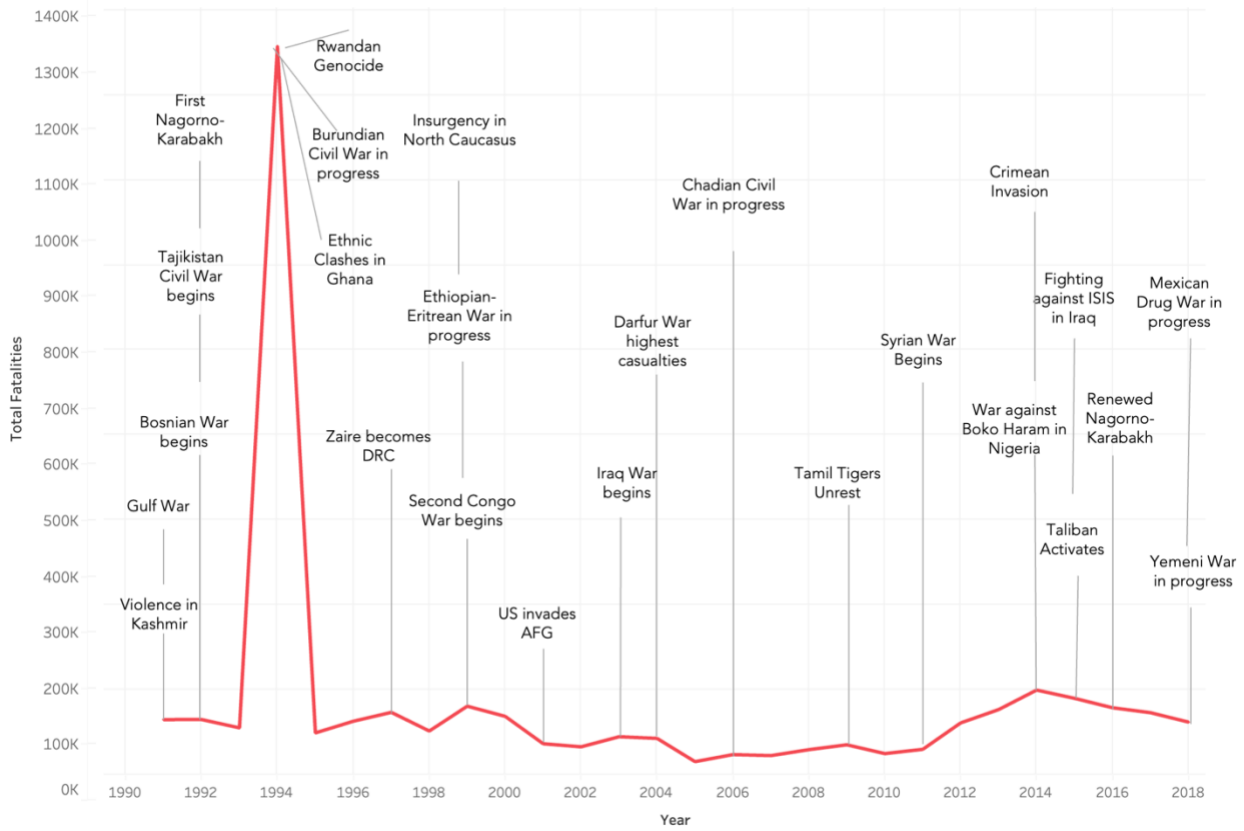


Figure 9: Total Number of Fatalities Over Time

Figure 10 below presents the average annual civil conflict duration (in days) per country. Consistent with the onset graph, the most prolonged conflict period was in 1991, with multiple conflicts occurring in Sub-Saharan Africa. For the remainder of the sample, the average number of conflict days remains

consistently lower at approximately 60 days a year. Similar to onset and severity, conflict duration slowly increases after 2010.

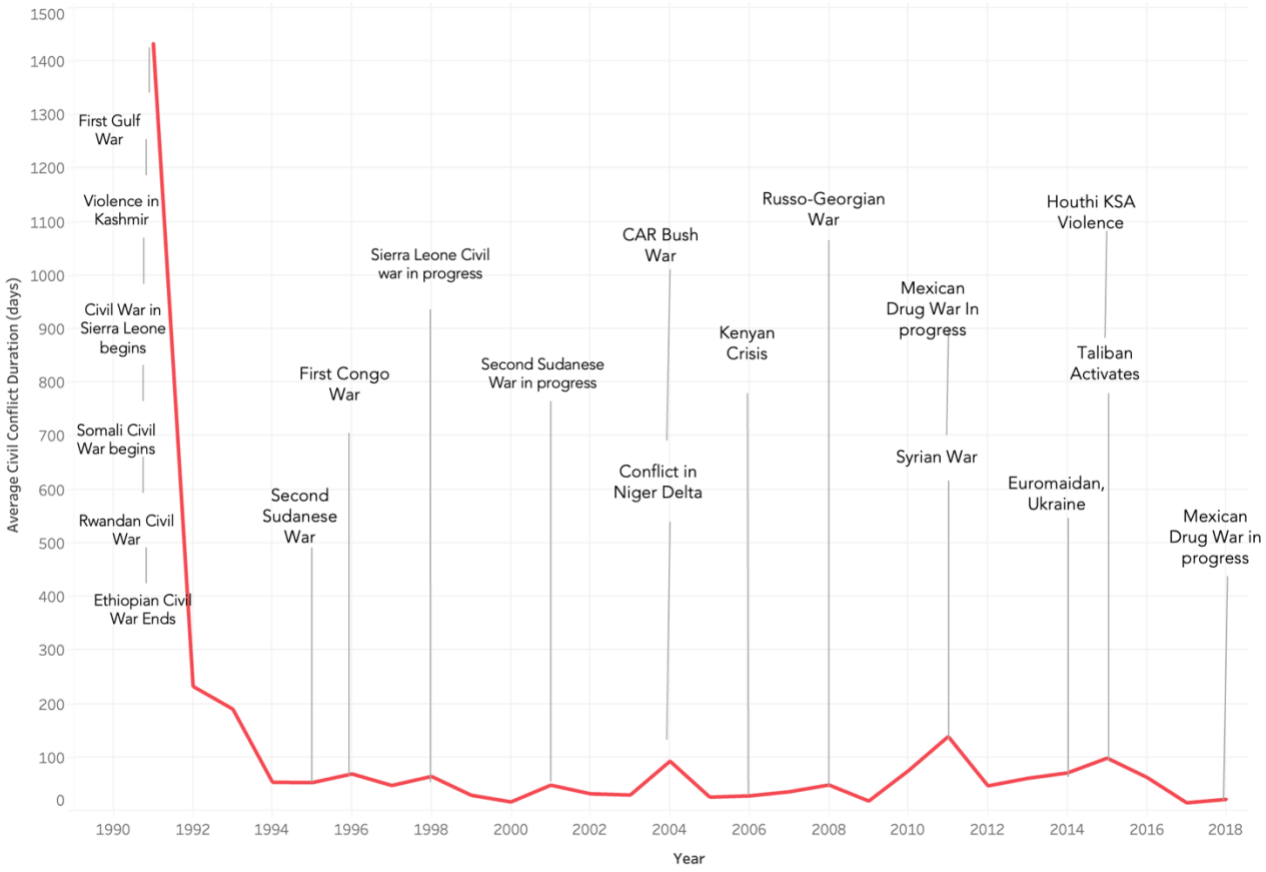


Figure 10: Average Civil Conflict Duration Over Time (days)

Figure 11 below shows the time series plot for total protests over time. The nonviolent protest plot significantly differs from the first three measures of violent conflict. While maintaining relatively steady levels before 2010, the frequency of protests increased substantially after 2010. Primarily attributed to Arab Spring (2010), it got exacerbated by Ukraine, North Africa, and the Middle East events.

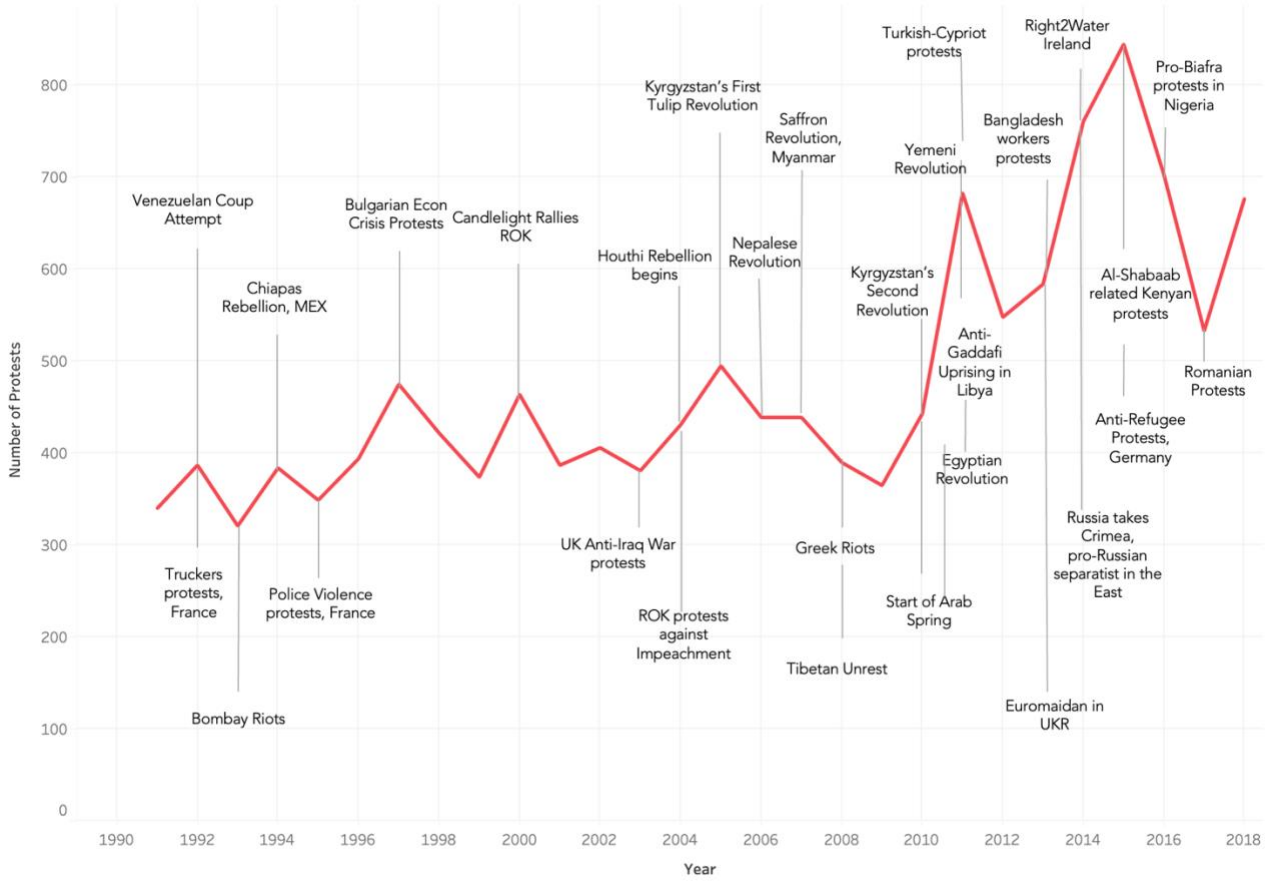


Figure 11: Total Number of Protests Over Time

Figure 12 below shows pairwise scatterplots between the three dependent variables, namely onset, fatalities, and duration. All three are strongly positively correlated. The relationship is linear and exhibits similar behavior across all three plots.

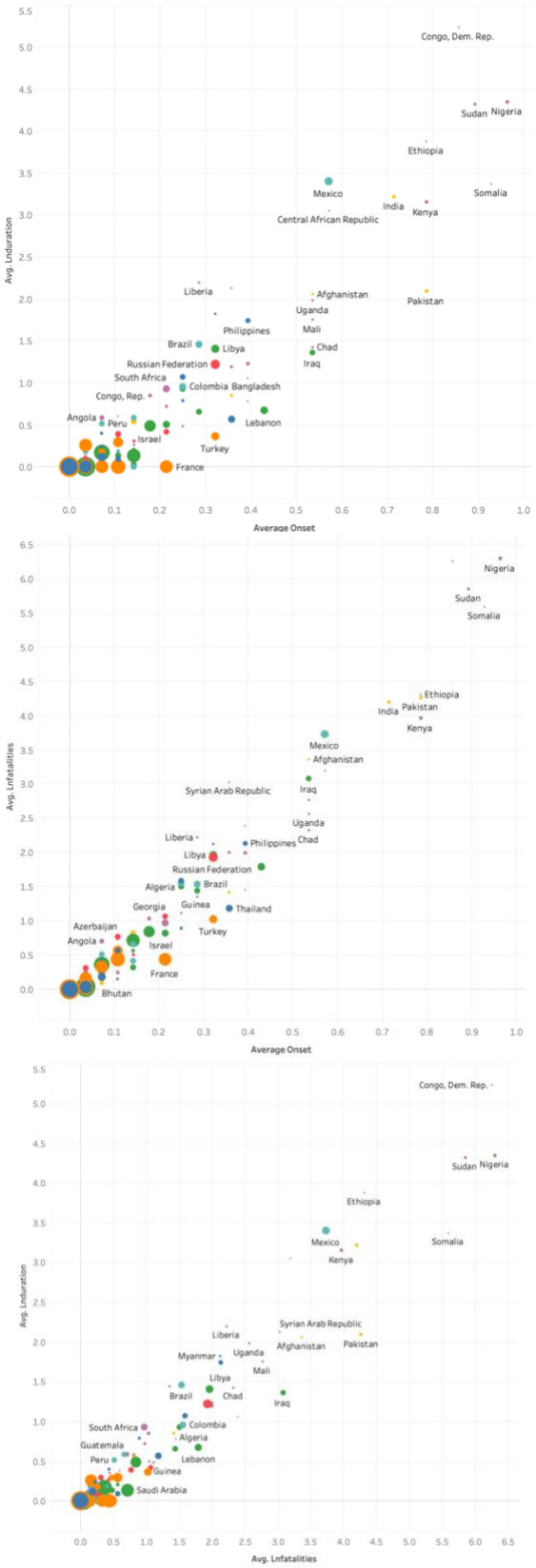


Figure 12: Pairwise Scatterplots of Onset, Fatalities, and Duration

Figure 13 below shows the pairwise scatterplot between the civil conflict onset and protests. According to the plot, there is no clear linear relationship between the two variables. UK and France experience the highest average number of protests but almost no severe violence incidences. While Western societies involve in a range of nonviolent events, they face little to no severe violence incidence. On the contrary, countries with numerous violence incidences, such as Nigeria, Sudan, Ethiopia, and Somalia, have a relatively low number of protests. This suggests that nonviolent protests behave differently compared to violent conflict.

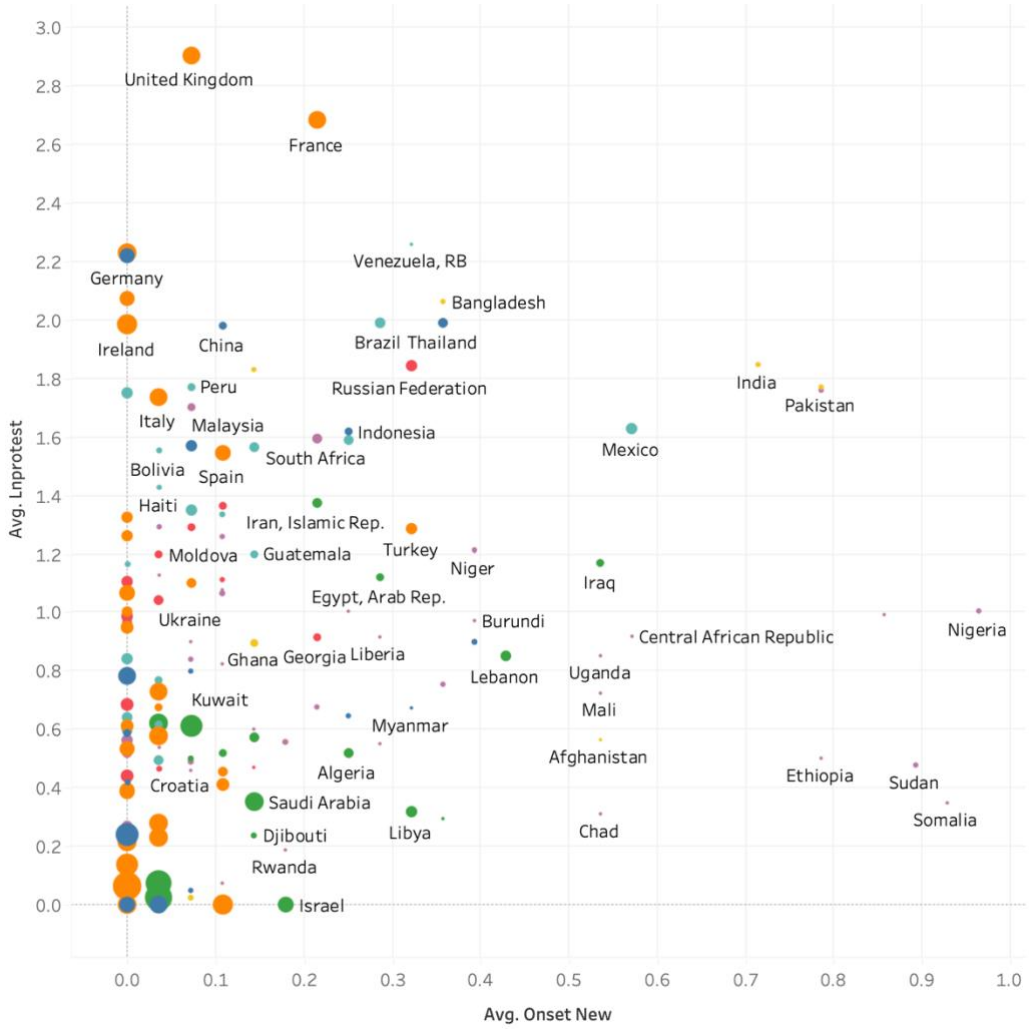


Figure 13: Pairwise Scatterplot Between Onset and Protests

Independent Variables

Table 2 below presents a summary statistics table for all 11 independent variables. Like the Summary Statistics table for DVs, it summarizes each variable's observations, mean, standard deviation, and min and max values. Unlike dependent variables, some independent variables have missing data.

Absolute Political Extraction (APE) is the first variable that ranges between 0.02 and 0.9. It has a mean of 0.5 and a standard deviation of 0.2. Based on these numbers, it approximately follows the normal distribution. The data is short of 107 observations.

Political repression is an ordinal categorical variable, ranging from 1 to 5. It has a mean of 2.6 and a standard deviation of 1.2. It is fully available across the sample.

Democracy is measured on a scale from 0-10, with a mean of 5.4 and a standard deviation of 3.9. A high standard deviation value indicates the skewness in the distribution. Democracy data is not available across every country in the given time frame.

Income equality is the percentage of income held by the bottom 50% of the population. The variable ranges from 3% to 29.1%, with a mean of 14.6% and a standard deviation of 4.6%. The data is slightly positively skewed and fully available across the sample.

Gender equality is measured as the female labor force participation rate ratio to the male labor force participation rate multiplied by 100. Higher values are indicative of a higher gender equality ratio. The results show that the variable ranges from 8.7 (Yemen in 2018) to 109.1 (Mozambique in 1997), with a mean of 70.6 and a standard deviation of 21.5. The distribution is negatively skewed. The variable is available across the entire sample.

Adjacent conflict measures the presence of cross-border violence in a given year and country. It equals 0 or 1, indicating the civil instability in one of the contiguous states. The mean of 0.7 suggests that, on average, one of the neighboring countries had a civil conflict. The standard deviation is 0.4. The data is fully available across the sample.

Economic development is measured via GDP per capita. The original value takes values between $437 (Mozambique, 1992) and $120,648 (Luxemburg, 2007). The variable is positively skewed and has missing observations. It undergoes a logarithmic transformation which improves the skewness and smooths variable behavior. Log GDP per capita ranges from 6.1 to 11.7, with a mean of 9.1 and a standard deviation of 1.2.

Economic growth is operationalized via the annual GDP per capita percentage growth rate. The log of the growth rate is taken for normalizing purposes, with the mean and standard deviation of 1. It ranges between -6.4 to 4.9. The data is not available for every country.

Commodity exports are measured as goods and services exports' percent share of the total GDP. The values range from 0.01 (Myanmar, 2000) to 229 (Singapore, 2008) with a mean of 38.6 and a standard deviation of 27.1. The data is not available for every country in the given sample.

Internet use is measured as the percentage of the population that has internet access. It ranges from 0 (South Africa, 1991) to 99.7 (Qatar 2018). The distribution is negatively skewed. The variable is only missing a few observations.

Finally, population size is measured in thousands.[20] It is available across the entire sample and ranges between 191 (Belize 1991) and 1,392,730 (China 2018). It is highly skewed, as seen from the mean of 39,546 and the standard deviation of 138,585. The log of population normalizes the original value and ranges from 5.3 to 14.1 with a mean of 9.2 and a standard deviation of 1.6.

[20] Actual population size/1000

Statistic	N	Mean	St. Dev.	Min	Max
APE	4,429	0.5	0.2	0.02	0.9
repression	4,536	2.6	1.2	1	5
democracy	4,312	5.4	3.9	0	10
income equality	4,536	14.6	4.6	3.0	29.1
gender equality	4,536	70.6	21.5	8.7	109.1
adjacent conflict	4,536	0.7	0.4	0	1
lnGDP per capita	4,536	9.1	1.2	6.1	11.7
lnGDP per capita growth	4,535	1.0	1.0	−6.4	4.9
commodity exports	4,146	38.6	27.1	0.01	229.0
internet	4,426	20.7	27.7	0.0	99.7
lnpopulation	4,526	9.2	1.6	5.3	14.1

Table 2: Independent Variables Summary Statistics

Figure 14 below shows a correlation plot for dependent and independent variables. As expected, the first three dependent variables, namely onset, fatalities, and duration are highly correlated. However, protest exhibits different behavior and is not strongly related to any of the three DVs (consistent with Figure 13 above). APE is inversely related to the first 3 DVs but has a weak negative relationship with Protests. Repression has a positive relationship with all four DVs, especially fatalities. However, it is inversely related to state capacity and development. Democracy has a weak negative association with onset, severity, and duration but a weak positive relationship with nonviolent protest. This preliminary finding confirms hypothesis H4.[21] Both income and gender equality are weakly negatively related to all dependent variables. However, the adjacent conflict has a positive relationship with all 4 DVs, though weaker for protests. Economic development, commodity exports, and the internet are negatively associated with the DVs. Lastly, the population is strongly positively related to all 4 DVs. As seen from the plot, economic development and APE are strongly positively related. VIF

[21] H4: Democracy has a negative impact on conflict onset, duration, and severity but a positive effect on protest frequency.

diagnostics show no major multicollinearity as the mean VIF is 1.77, which is below the acceptable threshold of 10, or an even more conservative threshold of 5. None of the variables exceed 4.[22]

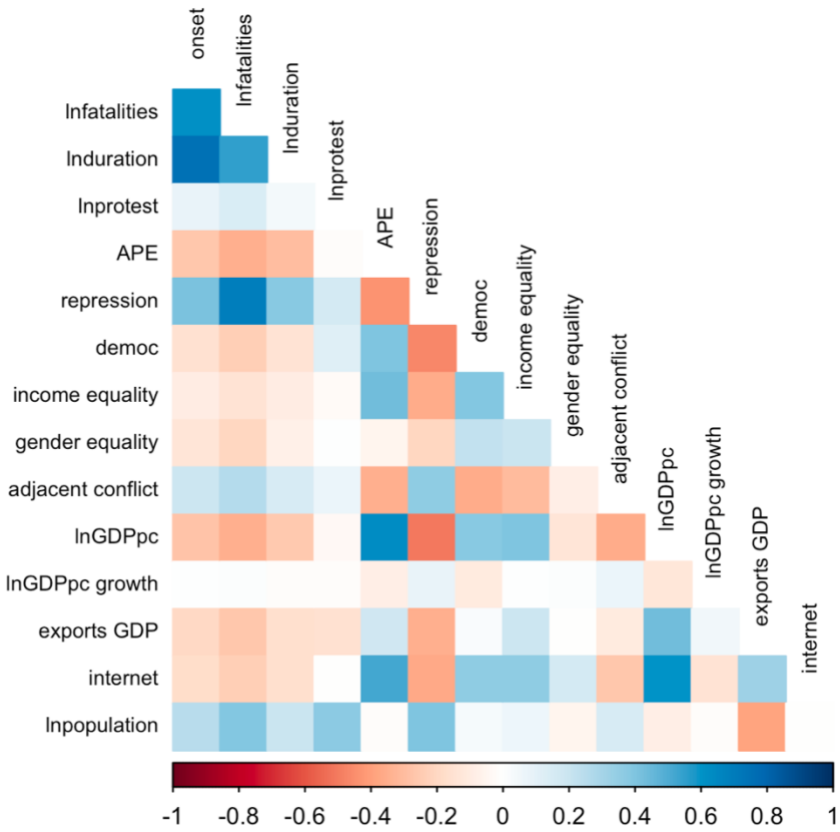


Figure 14: Correlation Plot of All Variables

Regional Classification

Figure 15 below shows the regional geographic country classification. It was adopted from the World Bank regional classification with two minor adjustments. First, former Soviet Union states were separated from the "Europe and the Central Asia" region, creating a separate "Former USSR" region. Second, North America joined Europe creating a new "Europe and North America" region. The rest is consistent with the World Bank classification (WDI, 2018).[23]

[22] See Figure xii in Appendix for VIF test details.
[23] There are 162 countries shown on the map. Grey/ white areas indicate countries excluded from the studied sample due to data availability (e.g., South Sudan, DPRK, Serbia).

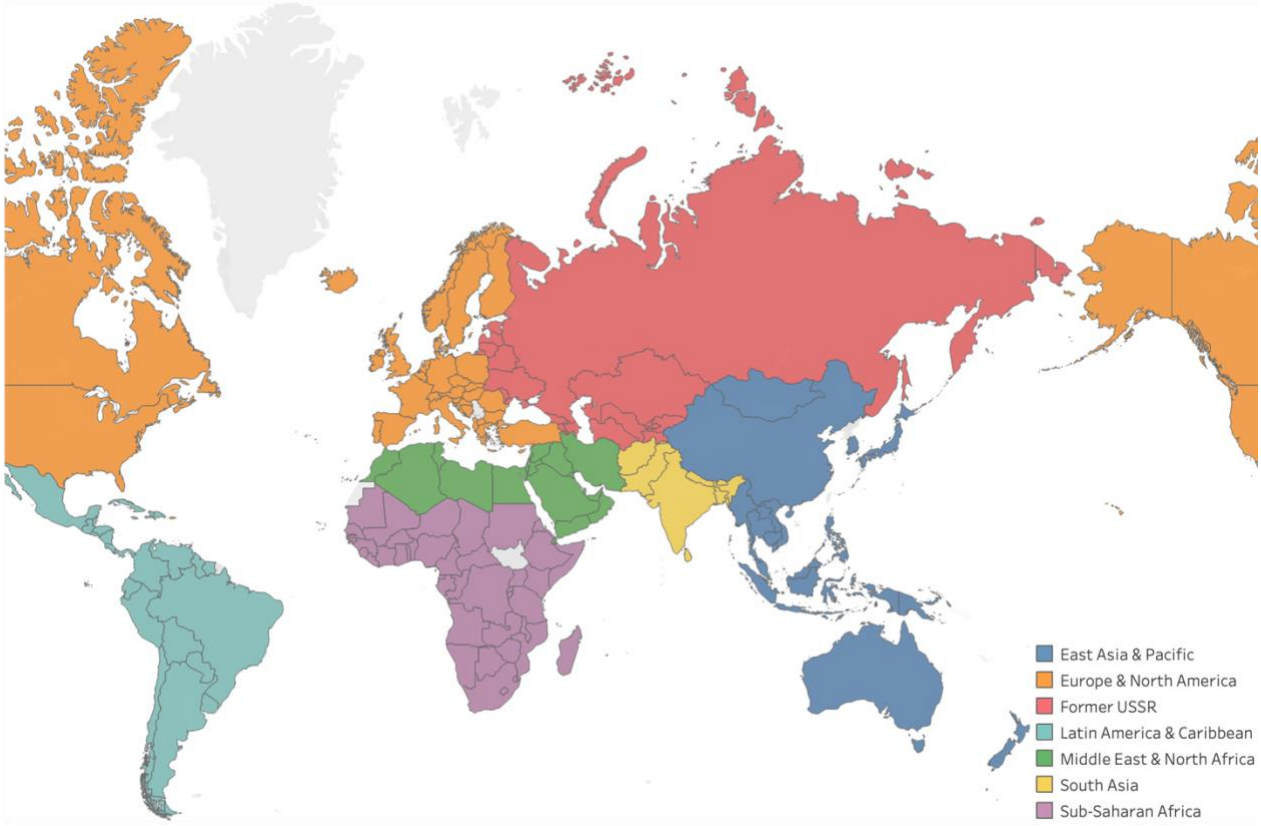


Figure 15: Regional Country Classification

Scatterplot graphs are used to understand each variable by region, detect potential outliers, and examine relationships between regressands and regressors. The section below shows pairwise scatterplot graphs for each dependent variable, namely the onset, severity, duration, and protest, and main independent variables.[24] All scatterplots follow the same format, where circle colors indicate region and the size reflects the average value of GDP per capita (unless stated otherwise). For each graph, Y-axis shows the average dependent variable value across the entire sample (1991-2018, 162 countries).

[24] Capacity, repression, democracy, income equality, gender equality, adjacent conflict, GDP per capita and population

Pairwise Scatterplots

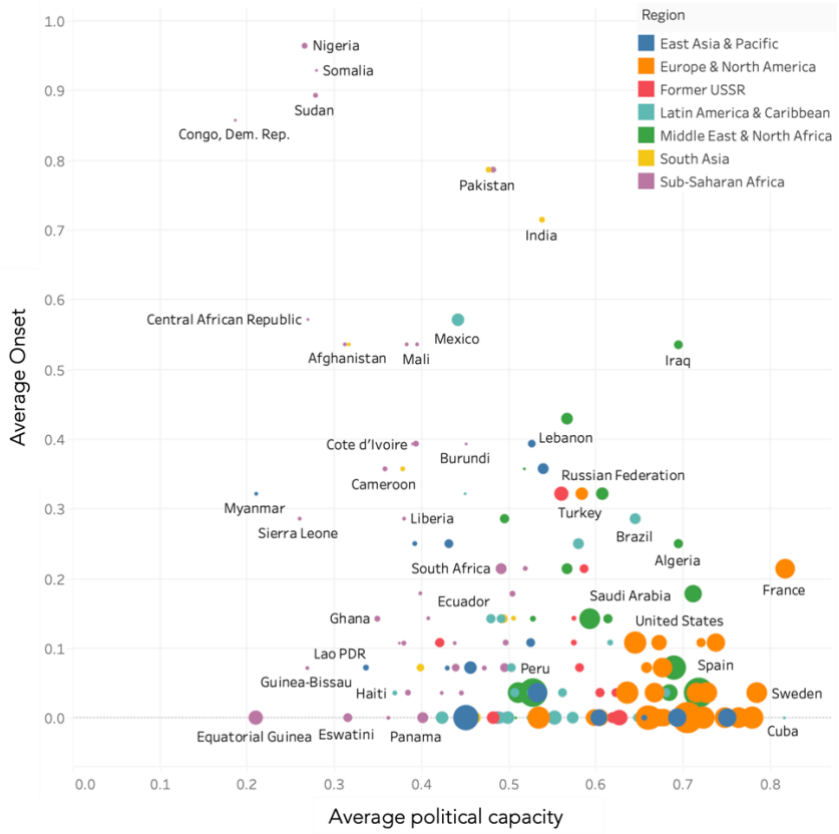
This subsection will provide pairwise scatterplots of key independent variables and all four development variables.

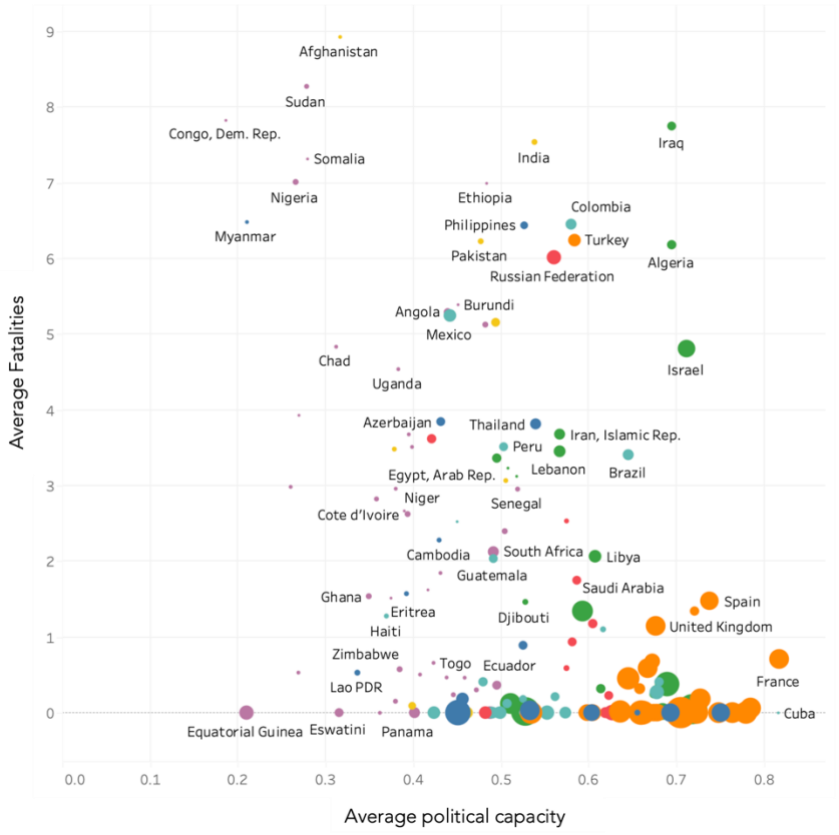
Political Capacity

Figure 16 below shows pairwise scatterplots of onset, severity, duration, and protest and the average APE. The X-axis indicates the average Absolute Political Extraction (APE) value, ranging from 0 to 0.9. The Y-axis shows each dependent variable correspondingly. The circle color distinguishes unique regions (see the legend), and the circle size indicates the level of economic development (average GDP per capita).[25]

A moderate negative relationship exists between state capacity and the average onset value. Europe and North America have the highest average APE across seven regions, followed by the Middle East (Qatar, Kuwait, Israel), North Africa (Algeria), and some East Asian (Japan) and the Pacific states (New Zealand). On average, these states had minimum violence initiation. On the contrary, Sub-Saharan countries such as Somalia, Nigeria, Sudan, DRC have the lowest average APE and experience conflict initiation. Additionally, more developed states are associated with lower onset values, confirming the literature (Collier and Hoeffler, 2004).

[25] The legends inside the graphs indicate regional breakdown (consistent with the previous map) and the average GDP per capita size.


Region
East Asia & Pacific
Europe & North America
Former USSR
Latin America & Caribbean
Middle East & North Africa
South Asia
Sub-Saharan Africa
Average Onset
Average political capacity
Nigeria
Somalia
Sudan
Congo, Dem. Rep.
Pakistan
India
Central African Republic
Mexico
Afghanistan
Mali
Iraq
Cote d'Ivoire
Burundi
Lebanon
Cameroon
Russian Federation
Myanmar
Turkey
Liberia
Sierra Leone
Brazil
Algeria
South Africa
France
Ecuador
Saudi Arabia
Ghana
United States
Lao PDR
Spain
Peru
Guinea-Bissau
Haiti
Sweden
Equatorial Guinea
Eswatini
Panama
Cuba


Average Fatalities
Average political capacity
Afghanistan
Sudan
Congo, Dem. Rep.
Somalia
Iraq
India
Nigeria
Ethiopia
Colombia
Philippines
Myanmar
Turkey
Pakistan
Algeria
Russian Federation
Angola
Burundi
Mexico
Chad
Israel
Uganda
Azerbaijan
Thailand
Iran, Islamic Rep.
Peru
Egypt, Arab Rep.
Lebanon
Brazil
Niger
Senegal
Cote d'Ivoire
Cambodia
South Africa
Libya
Guatemala
Saudi Arabia
Ghana
Spain
Eritrea
Djibouti
United Kingdom
Haiti
Zimbabwe
Togo
Ecuador
France
Lao PDR
Equatorial Guinea
Eswatini
Panama
Cuba

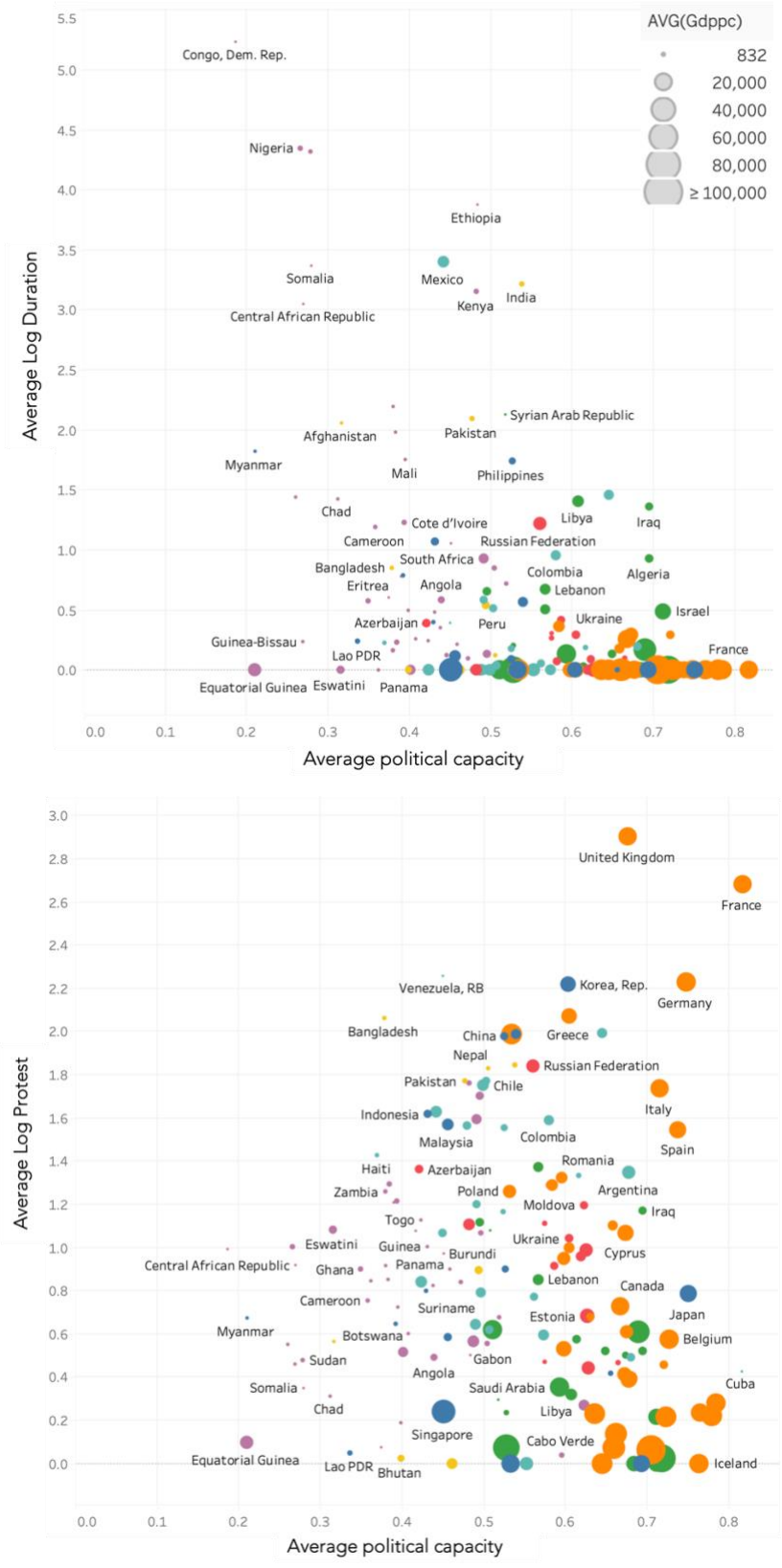


Figure 16: Scatterplots of DVs and Average Political Capacity

Conflict severity and state capacity have a moderate negative relationship, consistent with the onset. On average, politically capable Western states experience less severe violence. Some of the least developed and capable Sub-Saharan states, such as the DRC, Sudan, and Somalia, have the most violent conflicts. However, other Sub-Saharan countries with low state capacity, such as Guinea-Bissau, Equatorial Guinea, Eswatini, and Sierra Leone, have experienced nearly no violence, suggesting additional factors contribute to conflict severity.

State capacity and conflict duration have an inverse relationship, consistent with onset and severity. Unlike the first three DVs, protest and state capacity are somewhat positively related. For instance, highly capable Western states such as France, Germany, and UK experienced many demonstrations. In contrast, low-capacity states such as Chad and Gambia experienced little protest activity. Violence-prone countries (i.e., Sudan, Nigeria, DRC, and Somalia) had very few protests, implying that low-level unrest differs from high-level conflict. Overall, based on the first three graphs, Europe and North America has experienced the least violence compared to any region.

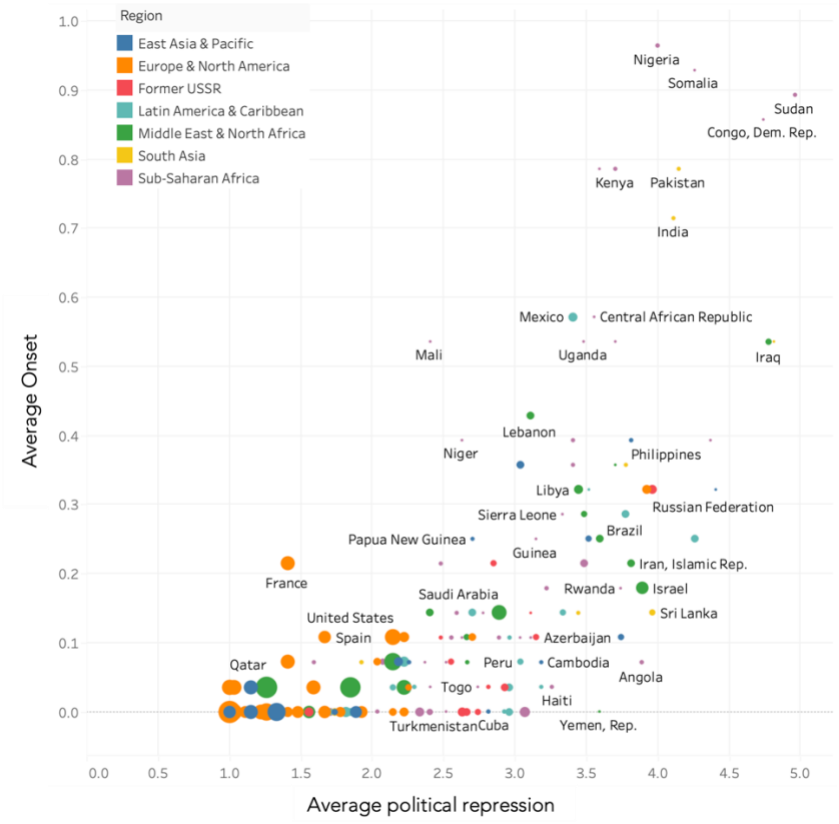
Political repression

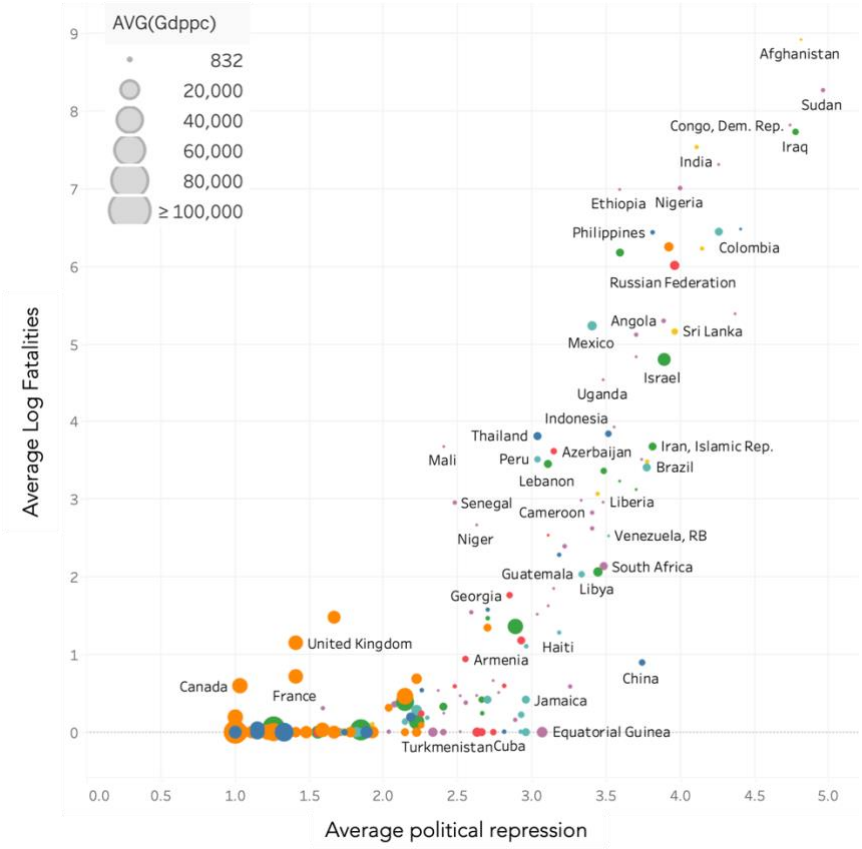
Figure 17 below presents four scatterplots of each dependent variable (Y-axis) and average political repression (X-axis, ranging from 1 to 5). Economically developed North American and European states have the lowest levels of repression, followed by Middle Eastern (Qatar, UAE, Kuwait, Bahrain), Pacific (NZ, Australia), East Asian (Japan, Singapore, ROK), and Sub-Saharan countries (Gabon, Eswatini, Guinea-Bissau). States with the highest repression are Sudan, DRC, Somalia, Nigeria (Sub-Saharan Africa), India, Pakistan, Afghanistan (South Asia), Iraq (Middle East), and Colombia (Latin America), among others. Repression and onset are strongly positively related. Several Sub-Saharan states, namely Sudan, DRC, Somalia, and Nigeria, have the highest levels of repression, the lowest

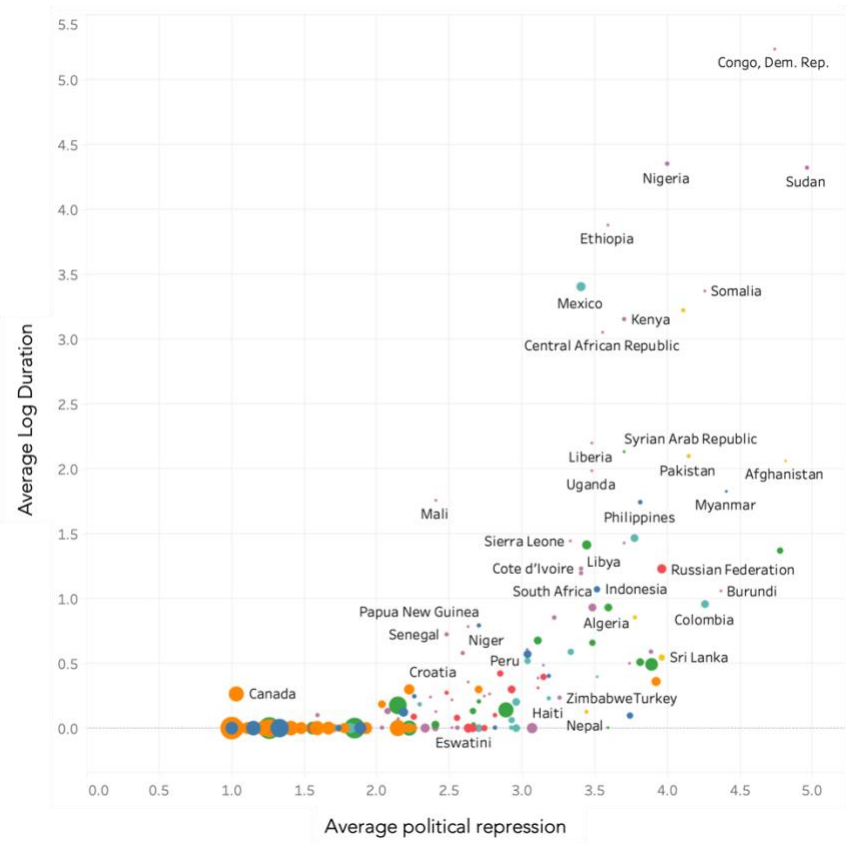
political capacity, and economic development (as seen from the last graph). They experienced the highest number of onsets.

Conflict severity and political repression are strongly positively related. Repression is a stronger predictor for severity than onset. Duration and repression are positively correlated, though not as strong as onset and severity. Sub-Saharan states, such as Sudan, DRC, Nigeria, Somalia, and Kenya, experienced severe and prolonged violence. Other countries with protracted violence are India and Mexico.

Repression and nonviolent protests have an unclear relationship. Many European states with low political repression (i.e., UK, France, Germany, Greece, and Ireland) had considerable protest activity. In contrast, states with high repression levels (i.e., Sudan, AFG, Somalia, and Myanmar) have had few protests. However, some European and Middle Eastern states (Oman, Belgium, Portugal) with low repression rates did not experience considerable protest activity.


Region
East Asia & Pacific
Europe & North America
Former USSR
Latin America & Caribbean
Middle East & North America
South Asia
Sub-Saharan Africa
Average Onset
Average political repression
Nigeria
Somalia
Sudan
Congo, Dem. Rep.
Kenya
Pakistan
India
Mexico
Central African Republic
Mali
Uganda
Iraq
Lebanon
Niger
Philippines
Libya
Russian Federation
Sierra Leone
Brazil
Papua New Guinea
Guinea
Iran, Islamic Rep.
France
Saudi Arabia
Rwanda
Israel
Sri Lanka
United States
Spain
Azerbaijan
Qatar
Peru
Cambodia
Angola
Togo
Haiti
Turkmenistan
Cuba
Yemen, Rep.


AVG(Gdppc)
832
20,000
40,000
60,000
80,000
≥ 100,000
Average Log Fatalities
Average political repression
Afghanistan
Sudan
Congo, Dem. Rep.
Iraq
India
Ethiopia
Nigeria
Philippines
Colombia
Russian Federation
Angola
Sri Lanka
Mexico
Israel
Uganda
Indonesia
Thailand
Azerbaijan
Iran, Islamic Rep.
Mali
Peru
Brazil
Lebanon
Senegal
Cameroon
Liberia
Niger
Venezuela, RB
Guatemala
South Africa
Libya
Georgia
United Kingdom
Haiti
Armenia
China
Canada
France
Jamaica
Equatorial Guinea
Turkmenistan
Cuba



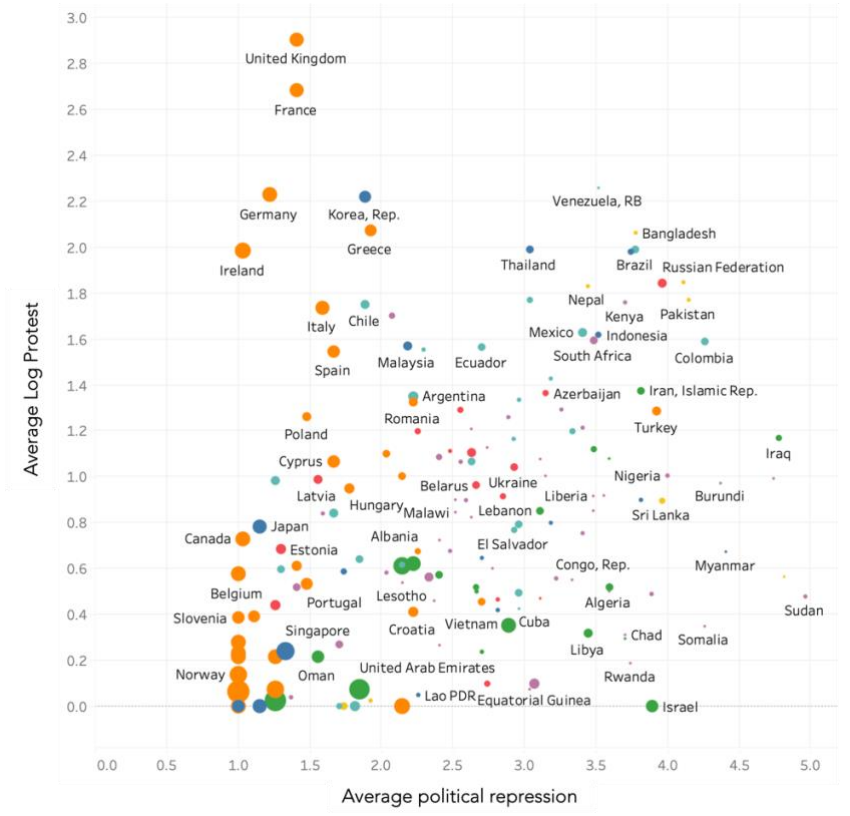


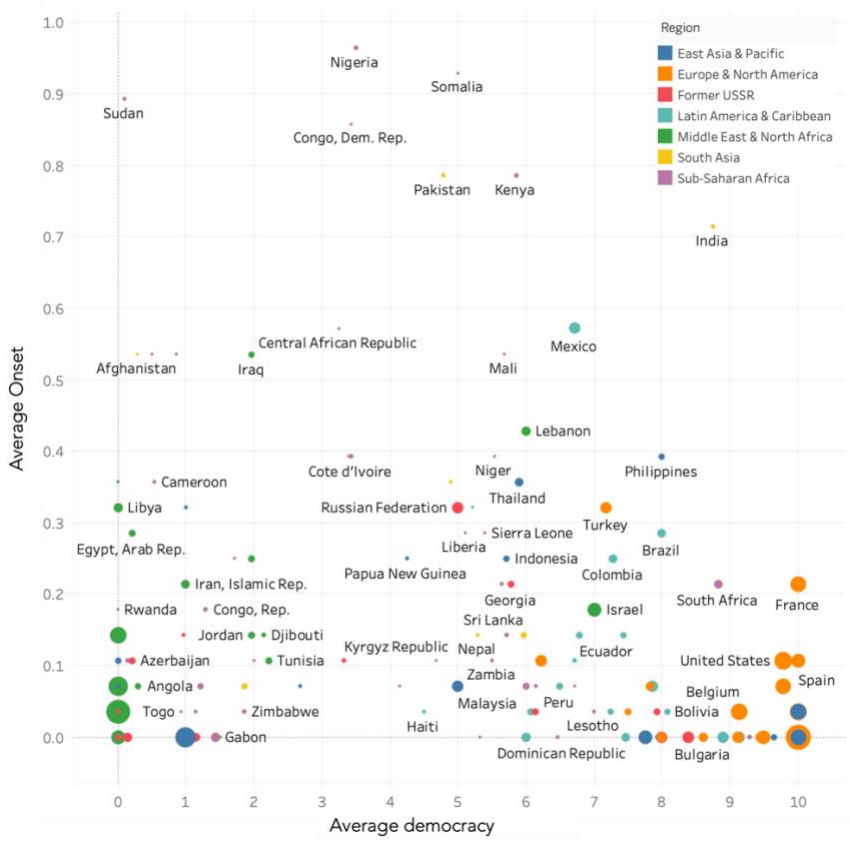
Figure 17: Scatterplots of DVs and Average Political Repression

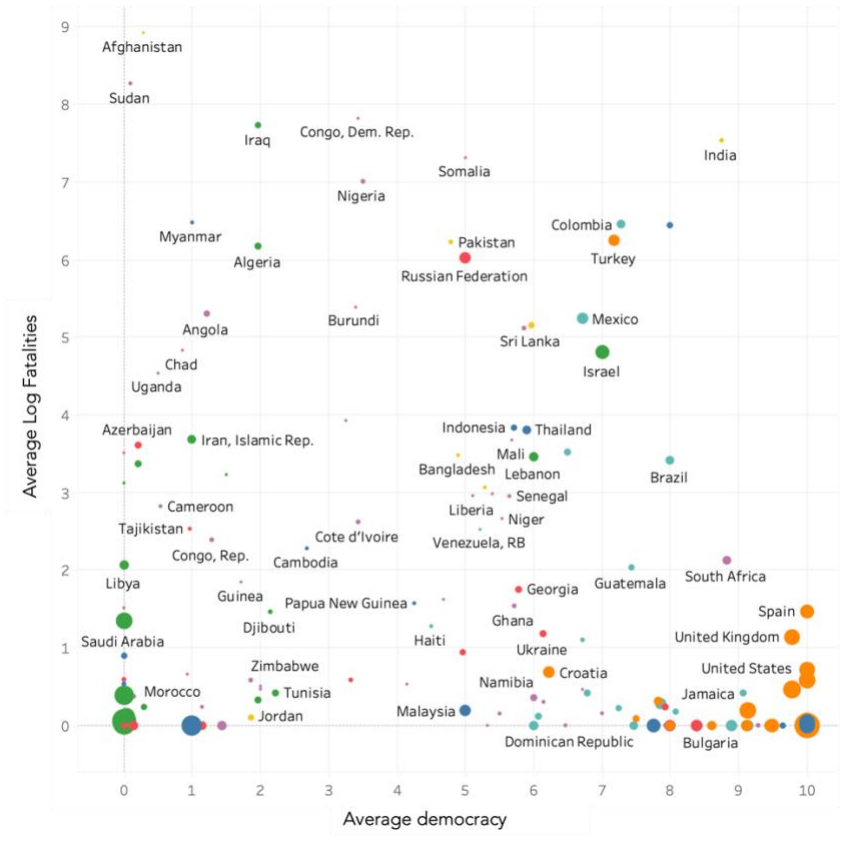
Democracy

At first glance, there is a weak negative relationship between democracy and violence onset. As expected, Western countries are highly democratic, whereas Middle Eastern and North Africa are the least democratic. There is no monotonic relationship between democracy and economic growth. Unlike the post-materialistic Western communities, highly developed Middle Eastern countries have the lowest levels of democracy.

Democracy and conflict severity do not have a clear relationship. Though the two seem inversely related, certain autocratic Middle Eastern and North African countries (Morocco, Saudi Arabia, Qatar) did not experience severe violence. On the other hand, more democratic India experienced extreme instances of violence. No clear relationship exists between democracy and duration either.

Unlike violent conflict, nonviolent protest has a weakly positive relationship with democracy. For instance, a relatively democratic ROK within its region (East Asia & the Pacific) experienced a higher number of protests. On the other hand, a less democratic Malaysia had fewer protest events. The level of democracy plays no role in European and North American states.


Region
East Asia & Pacific
Europe & North America
Former USSR
Latin America & Caribbean
Middle East & North Africa
South Asia
Sub-Saharan Africa
Average Onset
Average democracy
Nigeria
Somalia
Sudan
Congo, Dem. Rep.
Pakistan
Kenya
India
Central African Republic
Mexico
Afghanistan
Iraq
Mali
Lebanon
Cote d'Ivoire
Niger
Philippines
Cameroon
Thailand
Libya
Russian Federation
Turkey
Sierra Leone
Egypt, Arab Rep.
Liberia
Brazil
Indonesia
Papua New Guinea
Colombia
Iran, Islamic Rep.
Georgia
South Africa
France
Rwanda
Congo, Rep.
Israel
Sri Lanka
Jordan
Djibouti
Kyrgyz Republic
Nepal
Ecuador
Azerbaijan
Tunisia
United States
Zambia
Angola
Spain
Belgium
Malaysia
Peru
Togo
Zimbabwe
Bolivia
Haiti
Lesotho
Gabon
Dominican Republic
Bulgaria


Average Log Fatalities
Average democracy
Afghanistan
Sudan
Iraq
Congo, Dem. Rep.
India
Somalia
Nigeria
Myanmar
Colombia
Pakistan
Algeria
Turkey
Russian Federation
Burundi
Mexico
Angola
Sri Lanka
Chad
Israel
Uganda
Azerbaijan
Iran, Islamic Rep.
Indonesia
Thailand
Mali
Bangladesh
Lebanon
Brazil
Senegal
Cameroon
Liberia
Niger
Tajikistan
Venezuela, RB
Cote d'Ivoire
Congo, Rep.
Cambodia
South Africa
Libya
Guatemala
Georgia
Guinea
Papua New Guinea
Spain
Ghana
Djibouti
United Kingdom
Saudi Arabia
Haiti
Ukraine
Zimbabwe
Croatia
United States
Namibia
Morocco
Tunisia
Jamaica
Malaysia
Jordan
Dominican Republic
Bulgaria

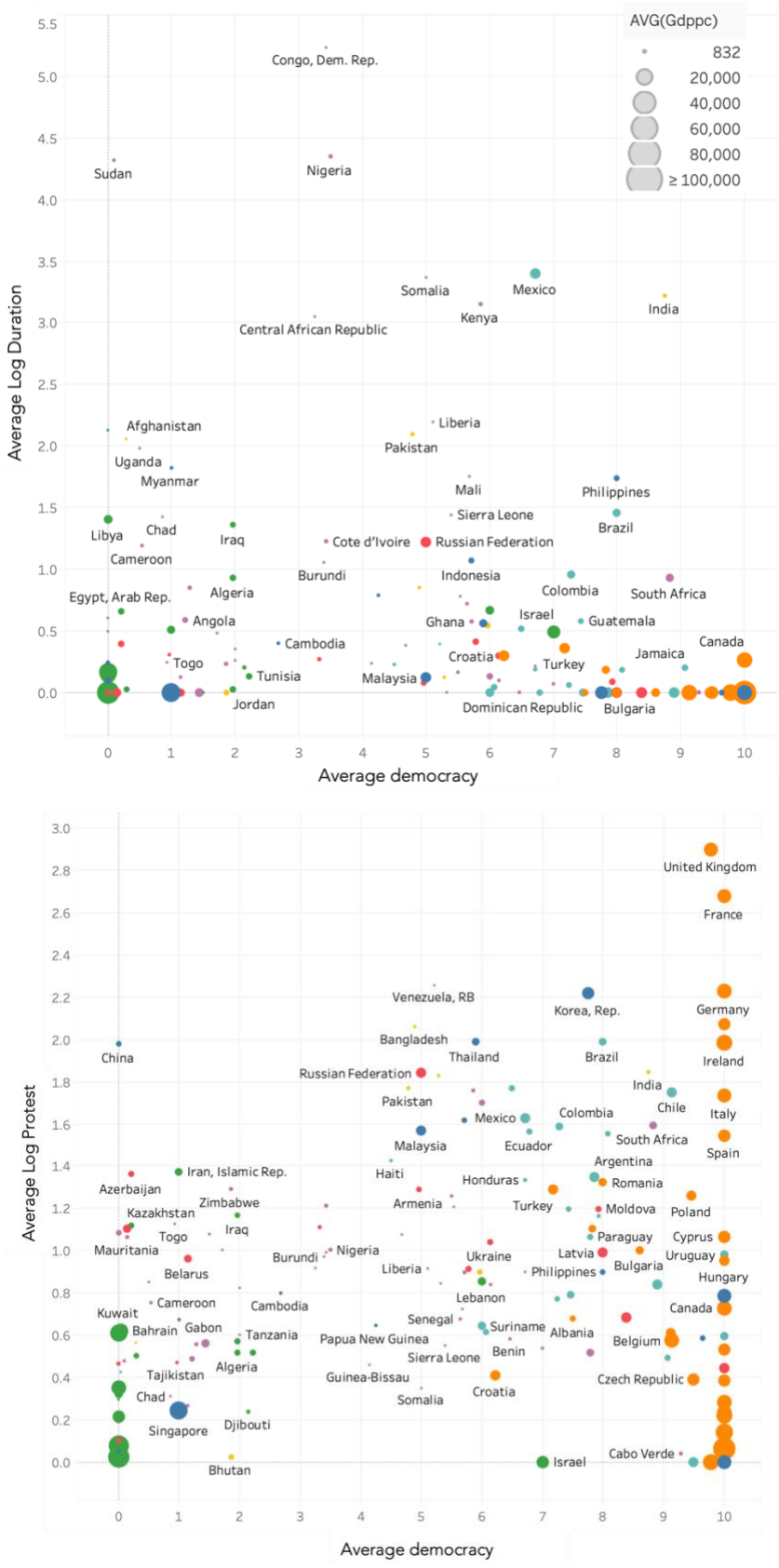


Figure 18: Scatterplots of DVs and Average Democracy

Recalling from the Literature Review chapter, Hegre (2001) finds that semi-democracies are the least stable regime type. They are at a higher risk of experiencing conflict than autocratic or democratic regimes. The scatterplots above did not confirm nor refute this statement. To further investigate this claim, a scatterplot of political capacity (APE) and democracy is examined in Figure 19 below. The X-axis indicates average democracy values ranging from 0 to 10. The Y-axis shows the average APE values ranging from 0 to 0.9. The bubble size indicates the total number of onsets.

According to the figure, democracy and APE have a U-shaped nonlinear relationship. Based on this graph, semi-democracies seem more prone to violence initiation. However, states with lower capacity experienced fewer onsets, regardless of the democracy level. This suggests that political capacity might be superior in predicting civil conflict onset, as opposed to regime type. Perhaps, Hegre (2001) omitted political capacity. The Results chapter will shed more light on this argument.

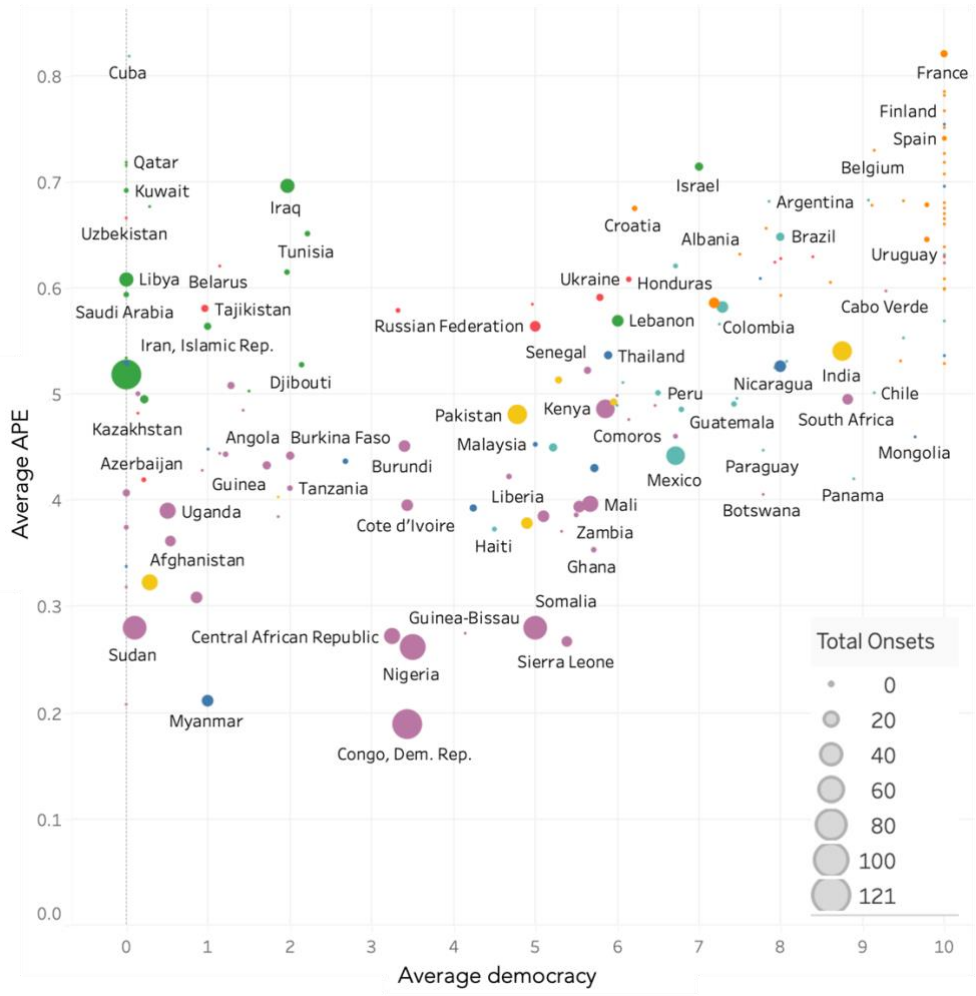
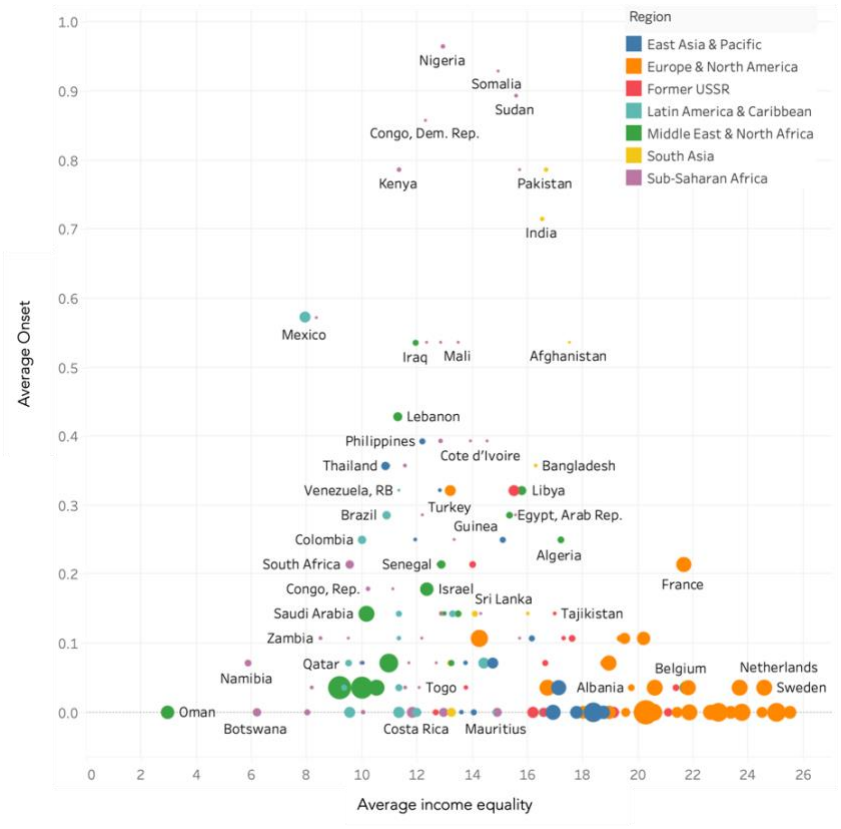


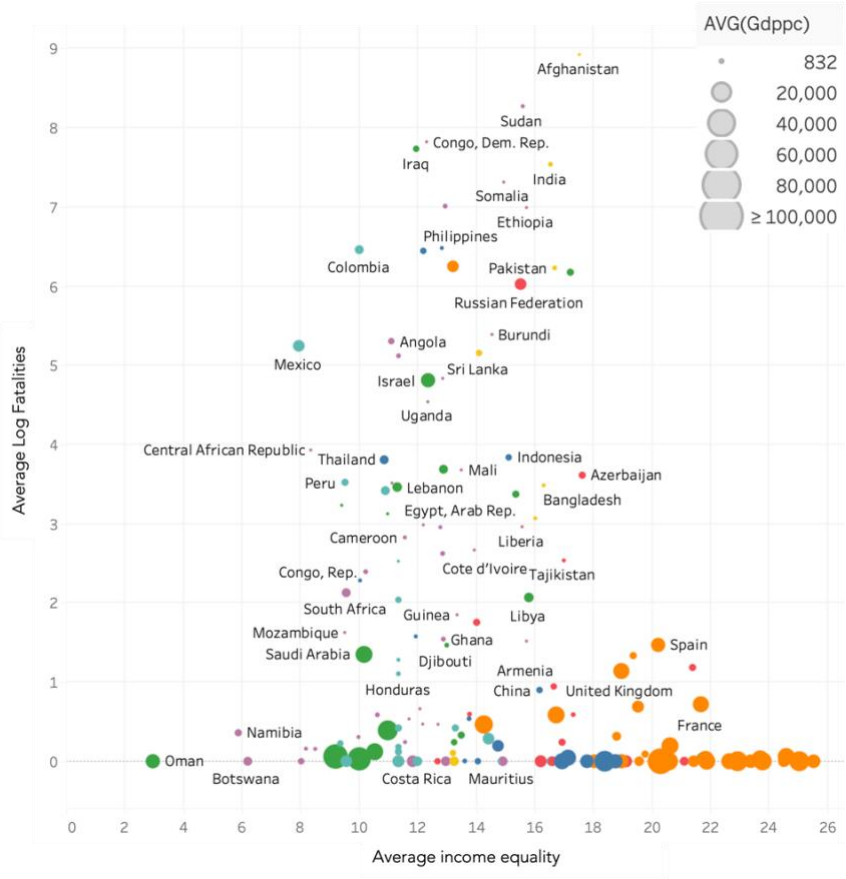
Figure 19: Scatterplot of Average APE and Average Democracy

Income Equality

Figure 20 below presents pairwise scatterplots between dependent variables and income equality.[26] Europe and North American states have the highest levels of income inequality. They are followed by East Asian and the Pacific states with quite high income equality levels (consistent with Feng, 2003). However, despite their high level of development, Middle East and North African countries such as Qatar, UAE, Kuwait, and KSA have low rates of income equality.

[26] Average income equality is equal to the average pre-tax income share of the bottom 50% of the population across 162 countries between 1991-2018.


Region
East Asia & Pacific
Europe & North America
Former USSR
Latin America & Caribbean
Middle East & North Africa
South Asia
Sub-Saharan Africa
Average Onset
Average income equality
Nigeria
Somalia
Sudan
Congo, Dem. Rep.
Kenya
Pakistan
India
Mexico
Iraq
Mali
Afghanistan
Lebanon
Philippines
Cote d'Ivoire
Thailand
Bangladesh
Venezuela, RB
Libya
Turkey
Brazil
Egypt, Arab Rep.
Guinea
Colombia
Algeria
South Africa
Senegal
France
Congo, Rep.
Israel
Sri Lanka
Saudi Arabia
Tajikistan
Zambia
Qatar
Belgium
Netherlands
Namibia
Togo
Albania
Sweden
Oman
Botswana
Costa Rica
Mauritius


AVG(Gdppc)
832
20,000
40,000
60,000
80,000
≥ 100,000
Average Log Fatalities
Average income equality
Afghanistan
Sudan
Congo, Dem. Rep.
Iraq
India
Somalia
Ethiopia
Philippines
Colombia
Pakistan
Russian Federation
Burundi
Angola
Mexico
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Bangladesh
Egypt, Arab Rep.
Cameroon
Liberia
Congo, Rep.
Cote d'Ivoire
Tajikistan
South Africa
Guinea
Libya
Mozambique
Ghana
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Armenia
Honduras
China
United Kingdom
France
Namibia
Oman
Botswana
Costa Rica
Mauritius

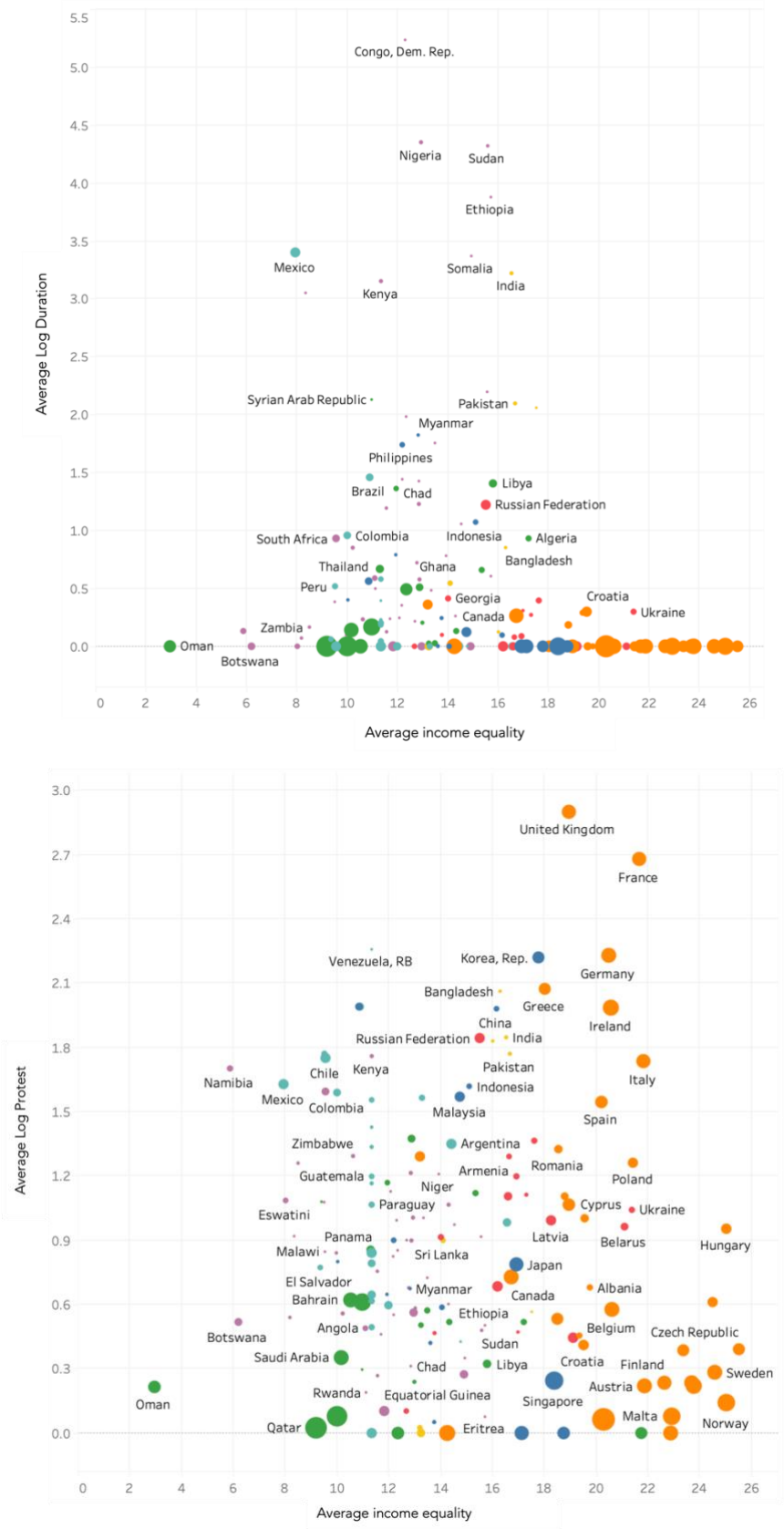


Figure 20: Scatterplots of DVs and Average Income Equality

There is no clear relationship between income equality and civil conflict (all four DVs). At first glance, regions with the highest income equality are Europe and North America, certain post-Soviet states (Belarus, Ukraine), followed by the Pacific (New Zealand, Australia), and East Asia (Singapore, ROK, Japan). Middle East & North Africa, Sub-Saharan Africa, and some Latin American states (i.e., Mexico) are among the regions with the highest income disparities. The outlier countries with disproportionately large violence, such as Sudan, Nigeria, Ethiopia, India, and Pakistan, have moderately low-income equality.

Nonviolent protests and income equality have a different dynamic compared to violent conflict. However, three is still no conclusive relationship between the two. This suggests that income equality is not a strong predictor for any measure of civil conflict.

Gender Equality

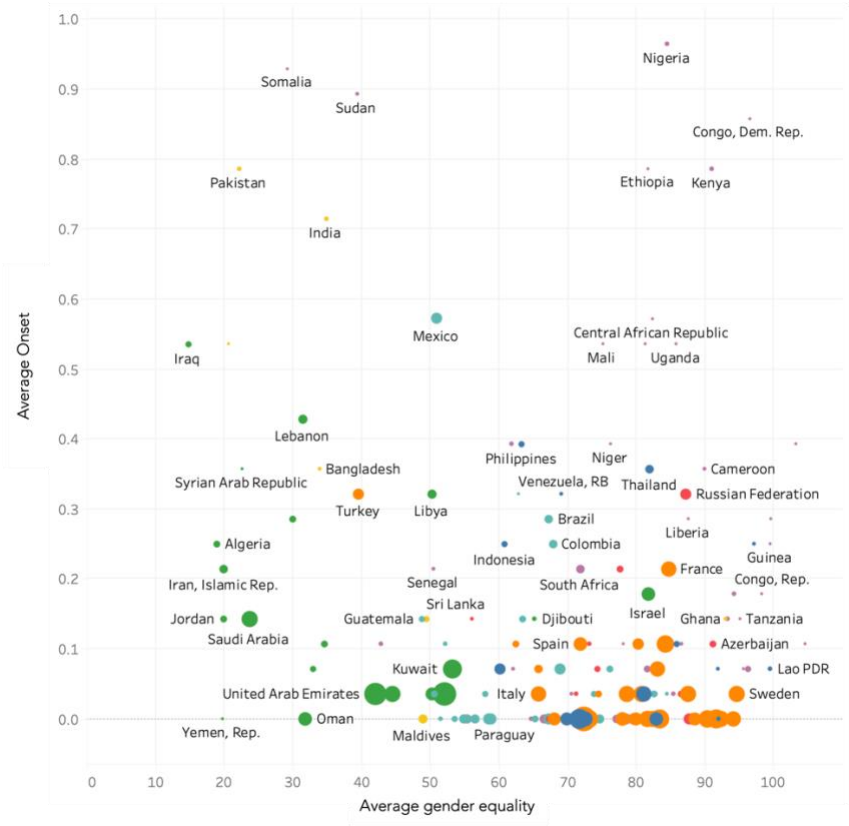
Figure 21 below shows the pairwise scatterplots of each DV (Y-axis) and the average gender equality (X-axis).[27] It is no surprise that Western states have attained higher levels of gender equality. However, less developed countries in Sub-Saharan Africa (Mozambique, Guinea, Burundi, the DRC) and East Asia & the Pacific (i.e., Laos and Papua New Guinea) sustained high gender equality. On the other hand, Middle Eastern and North African countries provide the least equal economic opportunities to females.

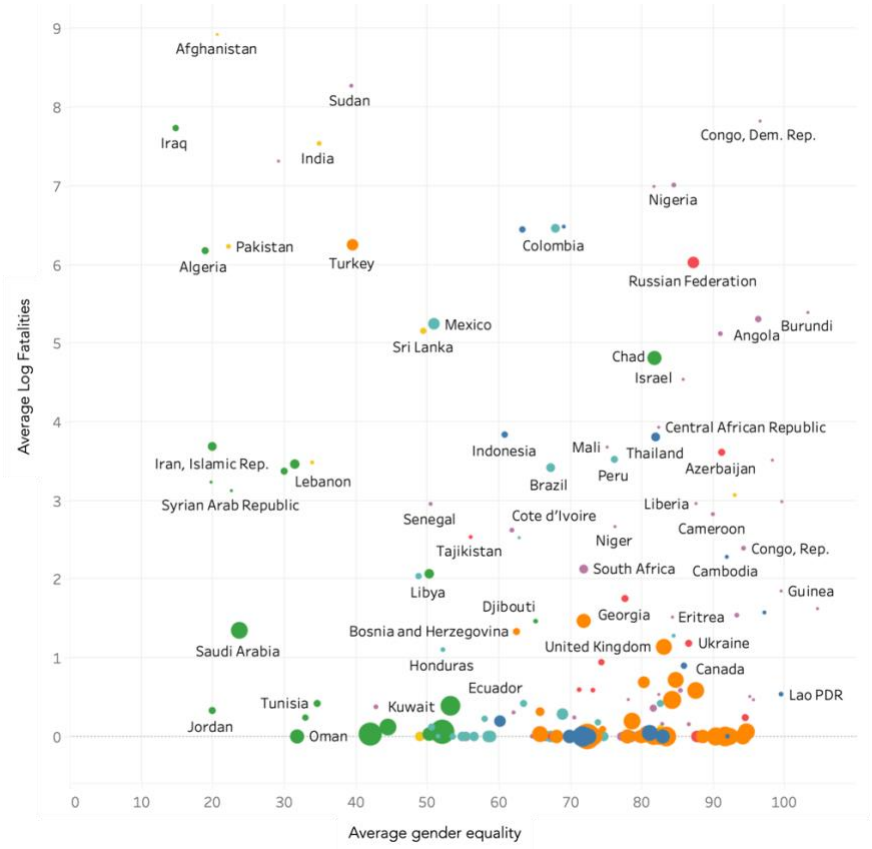
All four DVs have no apparent relationship with gender equality. For Instance, several Sub-Saharan states with high levels of gender equality, such as the DRC, Nigeria, and Ethiopia, have sustained extended periods of violence. Nevertheless, European and North American states had very few conflicts.

[27] Gender Equality = Female Labor Force Participation Rate/ Male Labor Force Participation Rate*100.

There is a slightly different dynamic between nonviolent protests and gender equality. On average, the two are slightly positively related. For instance, European states with the highest levels of equality (e.g., the UK, France, and Germany) had numerous protests. On the contrary, Middle Eastern and North African states, such as the KSA, UAE, Algeria, and Somalia, have practically had no protest activity. This relationship is inconclusive, as multiple other European states experienced no protests (Norway, Sweden, and Slovenia, among others). Like income equality, gender equality does not have a strong relationship with civil conflict measures. This preliminary finding rejects H5.[28]

[28] H5: Income and gender equality have a negative impact on conflict onset and severity.


Average Onset
Average gender equality
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
10
20
30
40
50
60
70
80
90
100
Nigeria
Somalia
Sudan
Congo, Dem. Rep.
Pakistan
Ethiopia
Kenya
India
Mexico
Central African Republic
Iraq
Mali
Uganda
Lebanon
Philippines
Niger
Syrian Arab Republic
Bangladesh
Venezuela, RB
Thailand
Cameroon
Russian Federation
Turkey
Libya
Brazil
Liberia
Algeria
Colombia
Indonesia
Guinea
France
Iran, Islamic Rep.
Senegal
South Africa
Congo, Rep.
Sri Lanka
Israel
Jordan
Guatemala
Djibouti
Ghana
Tanzania
Saudi Arabia
Spain
Azerbaijan
Kuwait
Lao PDR
United Arab Emirates
Italy
Sweden
Oman
Yemen, Rep.
Maldives
Paraguay


Average Log Fatalities
Average gender equality
9
8
7
6
5
4
3
2
1
0
0
10
20
30
40
50
60
70
80
90
100
Afghanistan
Sudan
Congo, Dem. Rep.
Iraq
India
Nigeria
Colombia
Pakistan
Algeria
Turkey
Russian Federation
Mexico
Angola
Burundi
Sri Lanka
Chad
Israel
Central African Republic
Indonesia
Mali
Thailand
Iran, Islamic Rep.
Azerbaijan
Peru
Lebanon
Brazil
Syrian Arab Republic
Liberia
Senegal
Cote d'Ivoire
Cameroon
Niger
Tajikistan
Congo, Rep.
South Africa
Cambodia
Libya
Guinea
Djibouti
Georgia
Eritrea
Bosnia and Herzegovina
Ukraine
Saudi Arabia
United Kingdom
Honduras
Canada
Ecuador
Lao PDR
Tunisia
Kuwait
Jordan
Oman

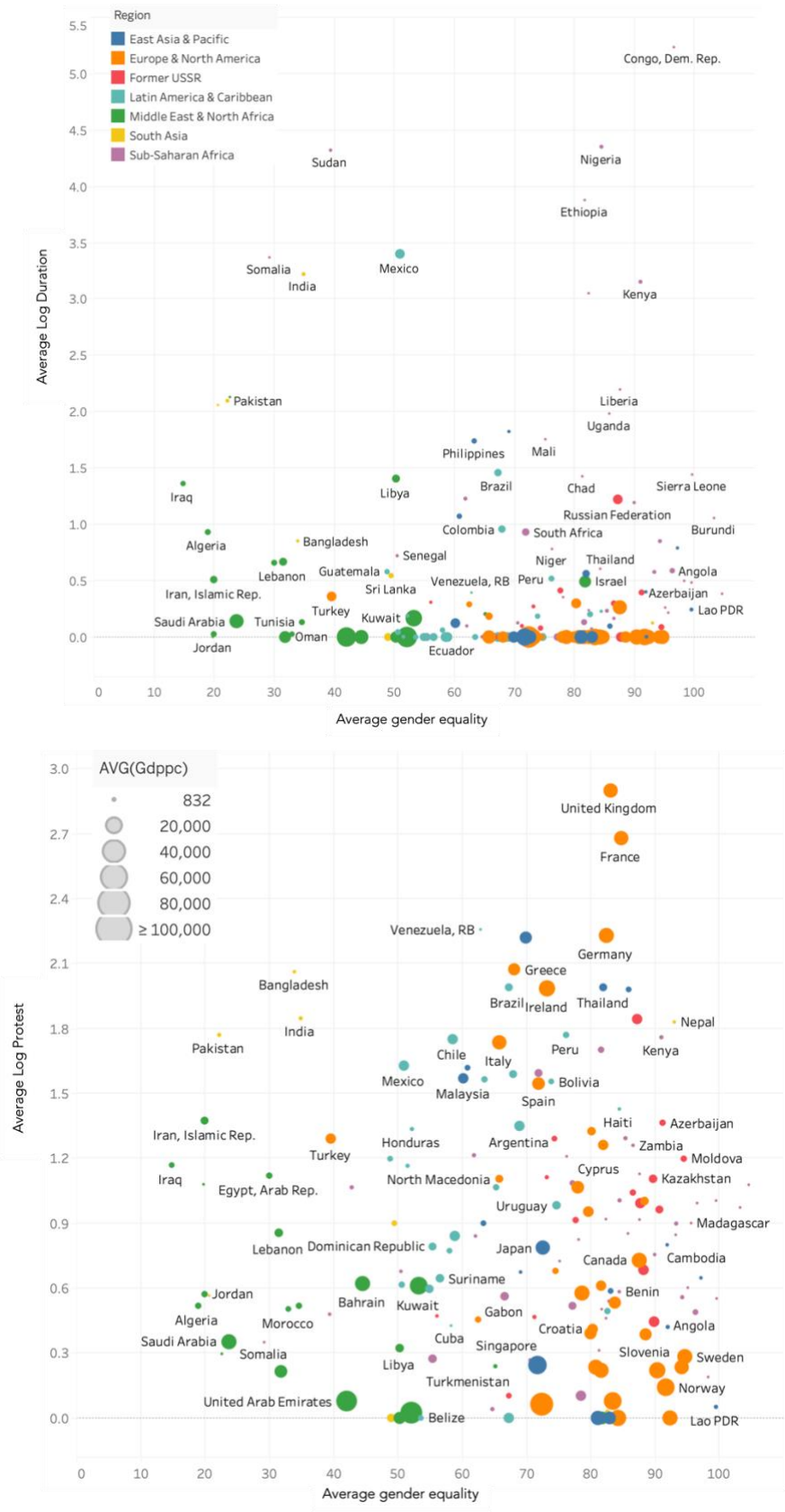


Figure 21: Scatterplots of DVs and Average Gender Equality

Adjacent Conflict

Figure 22 below shows the scatterplot graphs between DV's and average adjacent conflict. From the first three graphs, there is a positive nonlinear relationship between the presence of cross-border violence and the onset, severity, and duration of the conflict. As seen earlier, Somalia, Sudan, and Nigeria had the highest levels of violence. Moreover, at least one of their neighbors had an internal conflict. This suggests that conflict diffusion may have regional characteristics and should be further examined in the regional analysis.

There is no clear relationship between protests and neighbor violence. Europe and the North American region follow a positive relationship trajectory, where more protests are associated with cross-border violence.[29] However, this does not apply to other regions.

[29] E.g., France and Ireland had high protest activity, and higher values of adjacent conflict. Denmark, Slovenia, Croatia, among others, have almost no protests nor neighbor violence.


Region
East Asia & Pacific
Europe & North America
Former USSR
Latin America & Caribbean
Middle East & North Africa
South Asia
Sub-Saharan Africa
Average Onset
Average adjacent conflict
Nigeria
Somalia
Sudan
India
Mexico
Central African Republic
Lebanon
Philippines
Russian Federation
Brazil
Papua New Guinea
Algeria
Indonesia
South Africa
France
Israel
Ghana
Bosnia and Herzegovina
Spain
Honduras
Kyrgyz Republic
Netherlands
Jamaica
Lesotho
Oman
Argentina
Ireland
Mauritius
Botswana

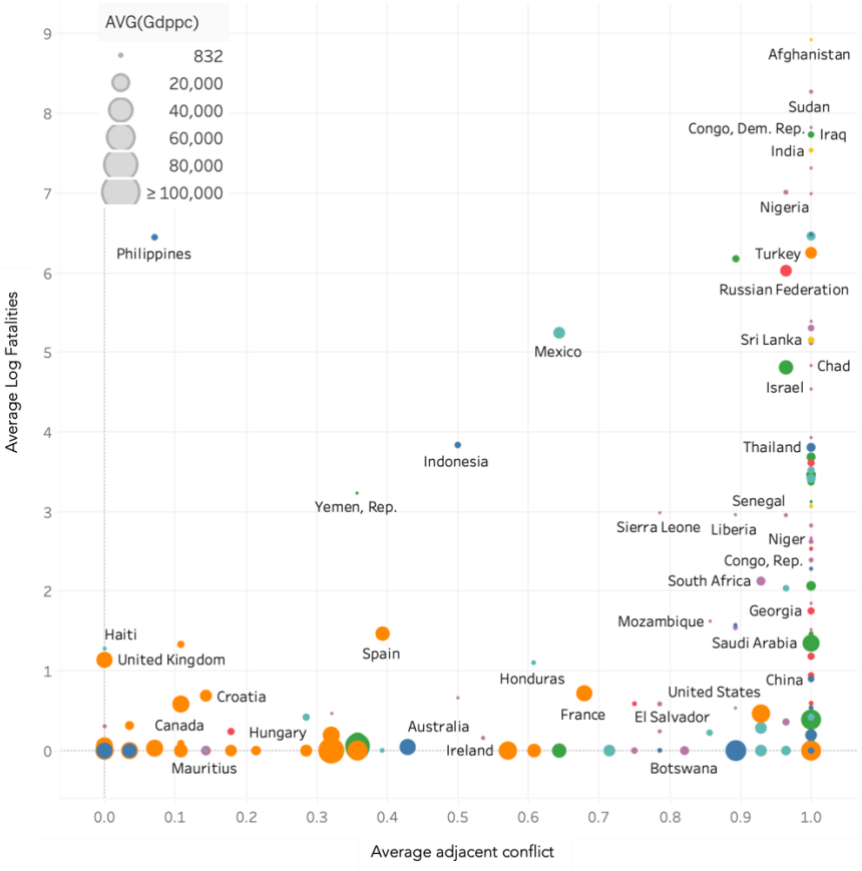
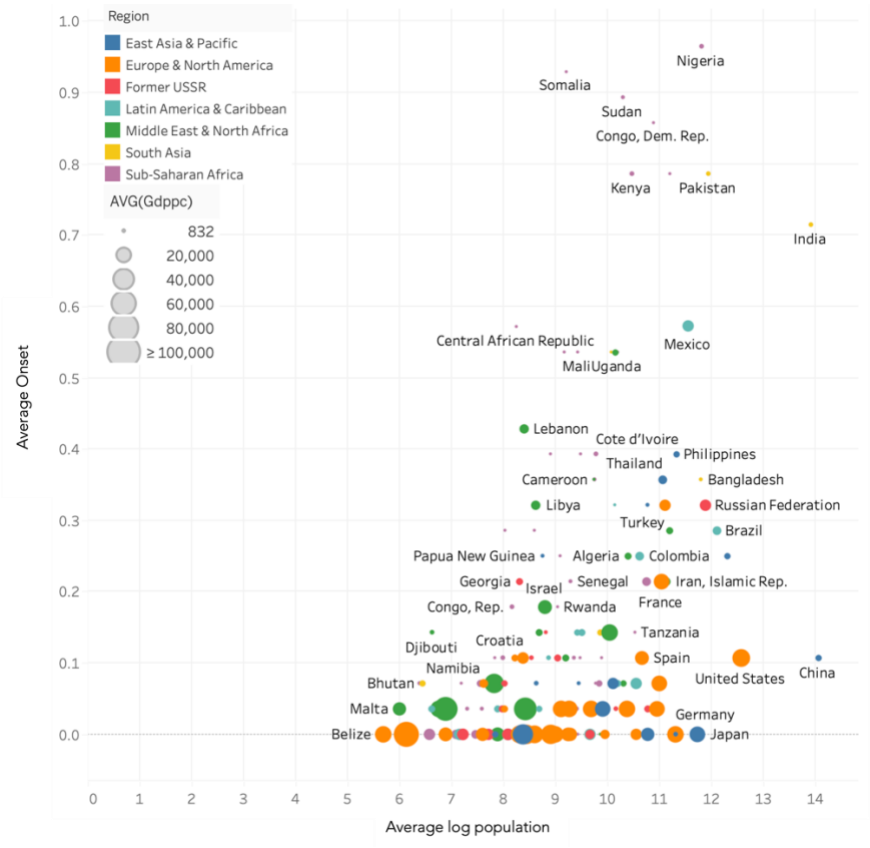

AVG(Gdppc)
832
20,000
40,000
60,000
80,000
≥ 100,000
Average Log Fatalities
Average adjacent conflict
Afghanistan
Sudan
Congo, Dem. Rep.
Iraq
India
Nigeria
Philippines
Turkey
Russian Federation
Mexico
Sri Lanka
Chad
Israel
Thailand
Indonesia
Yemen, Rep.
Senegal
Sierra Leone
Liberia
Niger
Congo, Rep.
South Africa
Georgia
Mozambique
Saudi Arabia
Haiti
United Kingdom
Spain
Honduras
China
United States
Croatia
France
El Salvador
Canada
Hungary
Australia
Ireland
Mauritius
Botswana

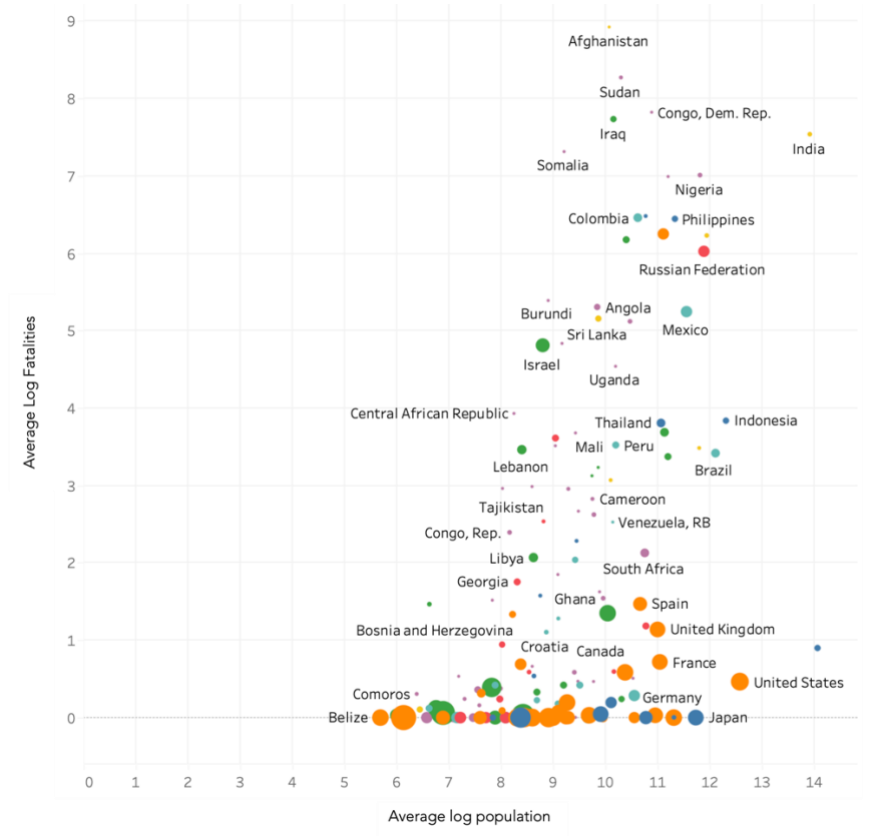
Figure 22: Scatterplots of DVs and Average Adjacent Conflict

Population

Finally, Figure 23 below shows the last set of pairwise scatterplots, revealing the relationships between DVs and the average log population. Nonviolent protests and population have the strongest positive relationship among the four DVs, followed by severity. Onset and duration are somewhat positively related to population, primarily due to a group of outliers (i.e., Nigeria, Pakistan, Ethiopia, Sudan, and the DRC). However, several medium-sized states, such as Liberia and CAR, sustained violence. On the other hand, other large states, such as the US and Japan, have not experienced prolonged violence. China is an outlier due to its largest population and low internal violent activity.

This chapter examined the underlying data in great detail to further use it in quantitative analysis. Several important observations follow. First, violent conflict measures, such as onset, severity, and duration, significantly differ from the nonviolent measure, namely protest. Second, not all theoretical variables have strong relationships with DVs. Certain variables, such as political repression, capacity, adjacent conflict, and population are more strongly associated the DVs. Third, the EDA identified region-specific effects that require further investigation via regional analysis.


Region
East Asia & Pacific
Europe & North America
Former USSR
Latin America & Caribbean
Middle East & North Africa
South Asia
Sub-Saharan Africa
AVG(Gdppc)
832
20,000
40,000
60,000
80,000
≥ 100,000
Average Onset
Average log population
Nigeria
Somalia
Sudan
Congo, Dem. Rep.
Kenya
Pakistan
India
Central African Republic
Mexico
Mali
Uganda
Lebanon
Cote d'Ivoire
Philippines
Thailand
Cameroon
Bangladesh
Libya
Russian Federation
Turkey
Brazil
Papua New Guinea
Algeria
Colombia
Georgia
Israel
Senegal
Iran, Islamic Rep.
Congo, Rep.
Rwanda
France
Djibouti
Croatia
Tanzania
Spain
Namibia
United States
China
Bhutan
Malta
Germany
Belize
Japan


Average Log Fatalities
Average log population
Afghanistan
Sudan
Congo, Dem. Rep.
Iraq
India
Somalia
Nigeria
Colombia
Philippines
Russian Federation
Burundi
Angola
Mexico
Sri Lanka
Israel
Uganda
Central African Republic
Thailand
Indonesia
Mali
Peru
Lebanon
Brazil
Cameroon
Tajikistan
Venezuela, RB
Congo, Rep.
Libya
South Africa
Georgia
Ghana
Spain
Bosnia and Herzegovina
United Kingdom
Croatia
Canada
France
United States
Comoros
Germany
Belize
Japan

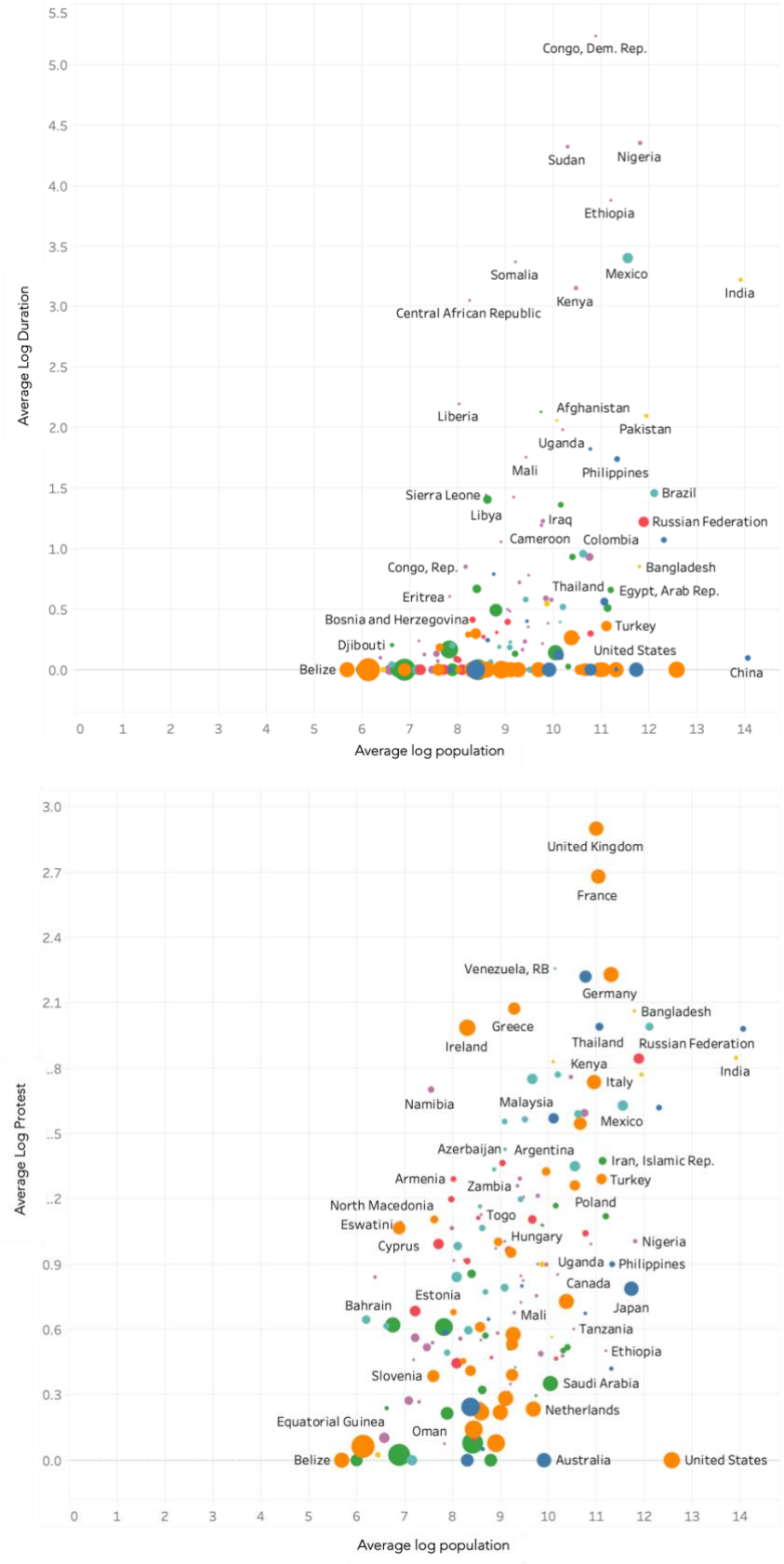


Figure 23: Scatterplots of DVs and Average Log Population

Chapter V. Results

The results chapter is perhaps the most critical piece of this dissertation. It lies at the core of the research by summarizing key model specifications and presenting the results for civil conflict measures that will further accept or refute the initially proposed hypotheses. Policy implications will follow afterward.

This chapter consists of two parts: global models and regional models. The former will examine the onset, severity, duration, and protest globally across 162 countries and 28 years. The latter will look at the same variables and models across specific regional geographic contexts.

Global Models

In this section, four dependent variables will be explored in detail. Six different model specifications for each DV are shown to test various theories of domestic conflict using political, social, economic, demographic, and technological variables. For each dependent variable, the appropriate econometric approach models each set of determinants to see their individual and combined impact on each measure of civil conflict. Model 1 is an autoregressive process of order one or AR (1) that explicitly tests for an endogenous process for each dependent variable. It answers research question #1.[30] Model 2 only includes political variables to see their unique impact on each dependent variable. Model 3 adds socioeconomic variables, and Model 4 introduces neighbor spillover or diffusion effects. Models 2-4 answer research questions 2a and 2b.[31] The fifth model adds all control variables, and Model 6 presents

[30] 1. Does the endogenous prior history of violence impact the current conflict?

[31] 2. What role do specific exogenous political, economic, and social factors have on civil conflict?

a) How do these specific effects hold when viewed separately?

b) What are the combined effects of these factors when viewed in the context of standard conflict controls?

complete model specification. It answers research question #2c.[32] As mentioned in the Methodology section above, a 5% significance level cutoff is used for hypothesis testing.

The first dependent variable is the onset of civil conflict, measured as a binary variable (1/ 0), so a pooled Probit Regression model is appropriate. The three remaining dependent variables, severity, duration, and protest, are continuous, therefore; Fixed Effects regressions are suitable to account for country heterogeneity. All continuous models use Panel Corrected Standard errors to correct autocorrelation and heteroscedasticity.

The Onset of Civil Conflict

The onset of violence is a dichotomous variable (1/ 0), necessitating limited dependent variable econometric estimation approaches such as Probit and Logit models. Overall, both models are very similar and belong to the generalized linear models (GLM) family (Kennedy 2008). Unlike linear OLS, Probit uses a cumulative standard normal distribution function of the linear combination of the independent variables to model the dependent variable's outcome. Hence, while the relationship between independent variables is linear, the link function is nonlinear. Probit coefficients reflect a change in Z associated with a one-unit increase in X. Thus, the outcome of Probit is a predicted probability. On average, the difference between the two methods is found negligible and generally became a matter of preference.

The first empirical estimation of conflict onset focuses on a pooled Probit approach. This is to see what effects are present at any time point across all countries in the sample, regardless of countries and time for dynamic effect. Beginning with a pooled approach is often the first step in assessing whether or not specific phenomena of interest exist within any cross-sectional time series or panel

[32] c) How do specific exogenous factors influence conflict in the presence of endogenous past conflict histories?

data set. Moreover, often the most simple and parsimonious models have proven robust and easy to interpret and explain (Gleditsch & Ruggeri 2010). Figure 24 below shows the full pooled Probit model specification for the onset of civil conflict. The data follows the panel format, where i is a country identifier, and t represents the year. The empirical specification includes one period lag of onset, followed by the three political factors (APE, repression, democracy), socio-economic factors (income and gender equality), and adjacent conflict. The remaining variables are standard controls found throughout the conflict literature, described in the Literature Review above. All independent variables are lagged for one period as a first cut guarding against endogeneity. Lagging IVs by one period may cope with this issue as the current onset level has no impact on the past political, economic and social factors.[33]

$$onset_{it} = \alpha_0 + \alpha_1 onset_{it-1} + \underbrace{\alpha_2 APE_{it-1} + \alpha_3 repression_{it-1} + \alpha_4 democ_{it-1}}_{\text{political}} + \underbrace{\alpha_5 incomeEquality_{it-1} + \alpha_6 genderEquality_{it-1}}_{\text{socio-economic}} +$$
$$\underbrace{\alpha_7 adjacentConflict_{it-1}}_{\text{diffusion}} + \underbrace{\alpha_8 log(GDPpc)_{it-1} + \alpha_9 log(GDPpcGrowth)_{it-1} + \alpha_{10} exportsGDP_{it-1} + \alpha_{11} log(population)_{it-1} + \alpha_{12} internet_{it-1}}_{\text{controls}} + \epsilon_{it}$$

Figure 24: Civil Conflict Onset Full Model Specification

The model equation represents the complete specification that addresses research question #2c. To answer questions 2a and 2b, each set of factors will be tested separately and demonstrated in the output table. First, the impact of political, economic, and social factors will be tested separately. Then, a full transdisciplinary model specification will be used to test all elements together in the same model. Question #3 will be answered by comparing and contrasting all four dependent variables' results.[34] Finally, Question 4 will be addressed via regional extension.[35]

[33] Subscript $_{t-1}$ notates a 1-period lag.
[34] Do the same factors hold for different levels of conflict onset, severity, duration, and protest as different dependent variables?
[35] Given the above, how do these factors change across different geographic regions?

Table 3 below presents Pooled Probit Regression results. Probit model coefficients are conditional probabilities based on mean effects, showing a change in Z associated with a one-unit increase in X. Model 1 is simply an autoregressive process of order one or AR (1). The coefficient is significant and high in magnitude, indicating that the history of conflict onsets considerably increases the likelihood of new conflict occurrence. Pseudo R^2 of 17% suggests that such an endogenous process of past onsets alone can explain about a fifth of the total variation in the dependent variable. The AUC of 0.72 indicates moderate classification performance.

Model 2 expands to the exogenous determinants of conflict onset, focusing on political features, such as state capacity, repression, and democracy. The model fit with these exogenous political determinants improves to 20%, implying that exogenous political variables are slightly more helpful in explaining the potential conflict initiation than just endogenous history alone. AUC increases by 0.09, resulting in 0.81. Here, capacity is the most critical variable (b=-1.298) as it is roughly twice the size of repression (b=0.534). Thus, higher state political capacity significantly drops violence incidence probability. This is consistent with the literature (Benson and Kugler 1998) partially confirming hypothesis H2[36]. Repression is positively associated with onset, implying that more repressive governments have a higher likelihood of conflict occurrence. Young (2012) finds that the more the governments repress their populations, the more likely they are to use brutal force against the people, thus generating dissident violence. Further evidence is found in the literature (Lichback, 1987; Tarrow, 1994; Gurr and Moore, 1997). Regime type is less relevant for conflict onset, evident from the low coefficient magnitude (b=0.013) and low significance level (90%).

Model 3 features political and socio-economic variables, slightly improving model fit (R2=20.7%). APE remains the most critical variable with an even higher magnitude of -1.652 (roughly three times the size of the political repression coefficient). With income and gender equality, the political capacity's

[36] H2: Political capacity has a negative impact on the onset, severity, and duration of the conflict.

role in conflict mitigation increases. Political repression maintains consistent results with the previous model (b=0.506). Democracy is significant at 95% and positively correlates with violence initiation, though the magnitude is negligible(b=0.017). Gender equality is negatively associated with potential violence incidence, with the most negligible impact (b= -0.006). Recalling from the literature, Regan and Paskeviciute (2003) find that female labor force limitations could hinder state capacity. The latter can significantly increase conflict onset. Model 3 results confirm this finding, showing state capacity's greater role in the presence of gender equality.[37] This is partially supportive of H5.[38]

[37] State capacity's impact on onset increases in the presence of gender equality, comparing APE coefficients between models 2 and 3 (-1.298 vs. -1.652).

[38] H5: Income and gender equality have a negative impact on conflict onset and severity

VARIABLES	(1) AR(1)	(2) Poli	(3) Socio-Econ	(4) Diffusion	(5) All Controls	(6) Full
$onset_{t-1}$	1.405***					0.718***
	(0.057)					(0.072)
APE_{t-1}		-1.298***	-1.652***	-1.562***	-1.011***	-0.741***
		(0.200)	(0.213)	(0.214)	(0.264)	(0.274)
$repression_{t-1}$		0.534***	0.506***	0.483***	0.310***	0.234***
		(0.030)	(0.030)	(0.030)	(0.038)	(0.039)
$democ_{t-1}$		0.013*	0.017**	0.025***	0.008	0.003
		(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
income $equality_{t-1}$			0.013*	0.016**	-0.007	-0.008
			(0.008)	(0.008)	(0.010)	(0.009)
gender $equality_{t-1}$			-0.006***	-0.006***	-0.007***	-0.005***
			(0.001)	(0.001)	(0.001)	(0.001)
adjacent $conflict_{t-1}$				0.505***	0.379***	0.337***
				(0.089)	(0.097)	(0.097)
lnGDP pc_{t-1}					-0.226***	-0.194***
					(0.046)	(0.047)
lnGDP pc $growth_{t-1}$					-0.047	-0.041
					(0.030)	(0.030)
exports GDP_{t-1}					-0.001	-0.001
					(0.002)	(0.002)
$internet_{t-1}$					0.003	0.003
					(0.002)	(0.002)
$lnpopulation_{t-1}$					0.189***	0.167***
					(0.025)	(0.025)
Constant	-1.405***	-2.060***	-1.616***	-2.093***	-1.105**	-1.248***
	(0.030)	(0.153)	(0.211)	(0.228)	(0.475)	(0.476)
Observations	4,374	4,074	4,074	4,074	3,710	3,710
Pseudo R^2	0.170	0.200	0.207	0.218	0.240	0.272
AIC	2994	2687	2667	2633	2294	2198
Log Likelihood	-1495	-1339	-1328	-1309	-1135	-1086
AUC	0.720	0.809	0.811	0.821	0.836	0.851

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Onset of Civil Violence, Pooled Probit Regression

Model 4 adds exogenous neighbor violence spillover or diffusion effects. R2 improves slightly (21.8%). The adjacent conflict is significant and has a substantial positive impact on potential conflict onset (similar magnitude as repression, b=0.505). This supports the 'bad neighbor' hypothesis (Weiner 1996). The regional analysis will later reveal whether region-specific spillover effects exist. Overall, all remaining variables, but income equality, maintain consistent behavior (income equality becomes significant, b=0.016).

Model 5 includes exogenous control variables, such as economic development, economic growth, commodity exports, internet use, and population. The model performance continues to improve (R2= 24%, AUC=0.84). However, APE, repression, and adjacent conflict have a reduced magnitude (b= -0.741, b= 0.234, b= -0.226). Among controls, economic development and population significantly impact onset (b= -0.226, b=0.189).

Model 6 presents a full model specification by including endogenous prior onset. It has the best performance, with a 10% higher pseudo R2 compared to the endogenous-only Model 1 (R2= 27.2%, AUC = 0.85). The results are strongly consistent with the previous models[39]. Political capacity remains the strongest predictor of new violence (b= -0.741). Lag onset is the second highest variable in magnitude (b=0.718). While increasing the government's capacity is essential in preventing potential violence initiation, the prior history of violence alone substantially increases the likelihood of new violence. Neighbor violence spillover effects are half as impactful as the past onset's (b=0.337). Political repression is smaller in magnitude compared to Model 5. However, it remains a significant predictor of new conflict (b=0.234). Economic development (b= -0.194) and population (b=0.167) are similar in magnitude and demonstrate consistent behavior with the previous model. Finally, gender equality remains significant across all five models despite its minor effects on violence.

The results indicate that civil conflict can be mitigated before its initiation. States should focus on political capacity and their populations' needs, including building equal economic opportunities for females. Playing a 'bad cop' can potentially exacerbate the conditions and increase the likelihood of violence. Moreover, enforcing strict border control is vital to keep neighbors' instability under close watch.

[39] This serves as a robustness check for independent variables.

The Severity of Civil Conflict

The severity of civil conflict is operationalized as the number of fatalities resulting from the intrastate conflict. Since the variable is continuous, different econometric estimation techniques are available. While sophisticated tools present value, often simple methods provide robust interpretable results. The most common linear model is an Ordinary Least Squares (OLS) regression. This dissertation will apply OLS modeling for robustness, interpretability, and explanation purposes.

Cross-sectional time series or panel structure of the data implies intercountry (between different countries) and intra-country (within the same country over time) variation. One of the major problems present in such data is unobserved heterogeneity, affecting both dependent variables and regressors. Fixed Effects estimator is one of the most common solutions to this problem.[40] It controls for the average differences across countries in observable and unobservable predictors. As a result, only within-country variation is left. This significantly reduces the threat of omitted variable bias (Kennedy, 2008). To function correctly, the Fixed Effects model requires a considerable within-group variation. OLS assumes error terms to be independent of one another and to have constant variance. The presence of non-spherical disturbances, such as heteroscedasticity and autocorrelation, produces inefficient estimators and erroneous statistical inferences due to wrong standard errors. To cope with these issues, panel-corrected standard errors (PCSE) were implemented. Beck and Katz (1995) compare techniques dealing with these issues, including Park's FGLS. Monte Carlo analysis shows that PCSE is more appropriate to use when problems of heteroscedasticity and autocorrelation are present (Beck and Katz 1995). The loss of efficiency is seldom present, and the estimates are consistent, especially since N= 4536.[41]

[40] Visit Appendix for the Hausman (1978) test results justifying the choice between Fixed Effects and Random Effects models.

[41] The article examines data typically analyzed by political scientists, implying that the current sample size is not large enough to cause problems with the PCSE method.

Below is the summary of the generalized empirical specification for the severity of the civil conflict. The model specification is identical to the onset model except for the lag DV, which is unique to this model. Similar throughout the literature, logarithmic transformation of fatalities is taken for normalization and estimation purposes of the data.

$$\log(\text{fatalities})_{it} = \beta_0 + \beta_1 log(fatalities)_{it-1} + \underbrace{\beta_2 APE_{it-1} + \beta_3 repression_{it-1} + \beta_4 democ_{it-1}}_{\text{political}} + \underbrace{\beta_5 incomeEquality_{it-1} + \beta_6 genderEquality_{it-1}}_{\text{socio-economic}} +$$
$$\underbrace{\beta_7 adjacentConflict_{it-1}}_{\text{diffusion}} + \underbrace{\beta_8 log(GDPpc)_{it-1} + \beta_9 log(GDPpcGrowth)_{it-1} + \beta_{10} exportsGDP_{it-1} + \beta_{11} log(population)_{it-1} + \beta_{12} internet_{i-1t}}_{\text{controls}} + \epsilon_{it}$$

Figure 25: Civil Conflict Severity Full Model Specification

Table 4 below shows Country Fixed Effects models results for the severity of civil violence.[42] Panel corrected standard errors are shown in parentheses.[43] This method corrects autocorrelation and heteroscedasticity.[44] The models are organized identically to the Onset models for easy comparison. At first glance, the severity of conflict is essentially an autoregressive process as the lag of the dependent variable explains most variation (the goodness of fit is even higher for Model 1 than Model 6). Overall, the RMSE is around 0.4[45].

Endogenous-only Model 1 has a high R2 of 79%, indicating that the prior history of casualties largely determines the current losses. The coefficient is the highest in magnitude among all models (b=0.585), meaning that severity of violence demonstrates cyclical behavior.

[42] Hausman Test for Fixed and Random Effects models found a significant difference between model coefficients, suggesting the use of the Fixed Effects Model (Prob > chi2 = 0.0000). Visit Appendix for details.
[43] Wooldridge (2002), Drukker (2003) test for serial correlation in panel models found the presence of autocorrelation (Prob > F = 0.0000). Visit Appendix for the output.
[44] Breusch Pagan/ Cook–Weisberg test for heteroskedasticity rejects the Null of constant variance (Prob > chi2 = 0.0000).
[45] Given that lnfatalities takes values between 0 and 14, with the mean of 0.79 and sd of 2.11, the RMSE of 0.4 is moderate.

VARIABLES	(1) AR(1)	(2) Poli	(3) Socio-Econ	(4) Diffusion	(5) All Controls	(6) Full
$\text{lnfatalities}_{t-1}$	0.585***					0.502***
	(0.0382)					(0.0405)
APE_{t-1}		-0.109***	-0.0980***	-0.0979***	-0.0725***	-0.0499**
		(0.0212)	(0.0222)	(0.0221)	(0.0237)	(0.0214)
repression_{t-1}		0.104***	0.104***	0.104***	0.0809***	0.0265
		(0.0212)	(0.0207)	(0.0207)	(0.0204)	(0.0168)
democ_{t-1}		-0.120***	-0.117***	-0.116***	-0.101***	-0.0611***
		(0.0264)	(0.0257)	(0.0255)	(0.0278)	(0.0232)
$\text{income equality}_{t-1}$			0.0664*	0.0660*	0.0382	0.0520
			(0.0346)	(0.0340)	(0.0359)	(0.0349)
$\text{gender equality}_{t-1}$			-0.212***	-0.209***	-0.151***	-0.172***
			(0.0437)	(0.0434)	(0.0440)	(0.0487)
$\text{agdjacent conflict}_{t-1}$				0.0105	0.00251	-0.00147
				(0.00939)	(0.00960)	(0.00873)
lnGDP pc_{t-1}					-0.0789	0.0139
					(0.0618)	(0.0558)
$\text{lnGDP pc growth}_{t-1}$					-0.0230**	-0.0201**
					(0.00892)	(0.00865)
exports GDP_{t-1}					0.0383	0.0531**
					(0.0246)	(0.0225)
internet_{t-1}					0.0236	0.0117
					(0.0148)	(0.0135)
$\text{lnpopulation}_{t-1}$					-0.141	0.0154
					(0.103)	(0.0750)
Constant	-0.168**	-0.171	-0.0401	-0.0478	0.291	0.00801
	(0.0809)	(0.127)	(0.128)	(0.128)	(0.258)	(0.191)
Observations	4,374	4,074	4,074	4,074	3,710	3,710
R^2	0.791	0.601	0.603	0.604	0.591	0.774
RMSE	0.431	0.431	0.430	0.430	0.420	0.418
Number of Countries	162	153	153	153	149	149

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Severity of Civil Violence, Country Fixed Effects Model with PCSE

Model 2 features only exogenous political variables and has a moderate R2 of 60%. Though significantly lower than the autoregressive model, political variables still demonstrate high predictive capability. Unlike in the onset model, democracy is reversely related to the severity. It is the strongest predictor among all political variables (b=-0.120). Consistently with the onset, political capacity negatively impacts severity (b= -109). This partially confirms H4.[46] Repression has a similar magnitude (b=0.104) and positively impacts conflict severity, consistent with the onset model.

[46] H4: Democracy has a negative impact on conflict onset, duration and severity but a positive impact on protest frequency.

Socio-economic Model 3 exhibits a similar model fit (R2 = 60%). Political variables demonstrate consistent results with Model 2. Compared to the onset models, gender equality has a more substantial negative impact on conflict severity. It is the most significant variable in magnitude (b= -0.212). This implies that unequal access to the labor force does not significantly increase the likelihood of new conflict onset but may potentially increase the severity of ongoing violence.

Diffusion Model 4 features neighbor violence diffusion. There are no changes in model fit (R2=60%, RMSE=0.43) nor variable behavior. Unlike the onset, the adjacent conflict has no impact on conflict severity.

Model 5 includes all control variables and exhibits little change in model fit (R2=59%, RMSE=0.42). Variable coefficients slightly drop in magnitude compared to the previous Model 4. Among controls, only economic growth negatively impacts conflict severity (b= -0.023).

Full Model 6 has the lowest bias among all six conflict severity models (RMSE=0.418) and a slightly lower fit than the autoregressive-only Model 1 (R2= 0.77). Endogenous lag fatalities have a consistently high coefficient of 0.502. All other variables, but repression, maintain consistent results across. In the presence of an endogenous history of violence, government repression has no impact on the current level of violence severity. Gender equality remains the second highest variable in magnitude (b = -0.172). Democracy has suppressive effects on violence severity (b = -0.061), consistent with the literature (Hegre 2001, Benson and Saxton 2008). Unlike in the previous Model 5, commodity exports significantly positively affect the severity (b = 0.053).

Based on the above results, little can be done to prevent conflict once it is initiated. Endogenous history will reinforce the current violence. Though capable and democratic states with more equal economic opportunities for females can expect less severe violence, past violence severity remains the main driving factor of the current casualties.

These findings conflict with the common greed and grievance-based civil war literature. The results indicate that while exogenous political, social, and economic factors matter for the severity, endogenous processes have the most considerable impact on future escalation, targeting policies to prevent new conflict at its root rather than battling the ongoing violence once it's initiated. Violence prevention beforehand should be a priority.

The Duration of Civil Conflict

A third way of analyzing civil conflicts is via duration. Duration is measured by the number of days a state is engaged in civil conflict per year. Unlike the first two measures, duration helps understand what factors sustain violence over time. This information allows states better allocate their resources to lessen the toll on society from protracted conflicts. The duration model follows the exact specification of the two models above. A Fixed Effects model with panel-corrected standard errors is used as well.

$$\log(\text{duration})_{it} = \gamma_0 + \gamma_1 log(duration)_{it-1} + \underbrace{\gamma_2 APE_{it-1} + \gamma_3 repression_{it-1} + \gamma_4 democ_{it-1}}_{\text{political}} + \underbrace{\gamma_5 incomeEquality_{it-1} + \gamma_6 genderEquality_{it-1}}_{\text{socio-economic}} +$$
$$\underbrace{\gamma_7 adjacentConflict_{it-1}}_{\text{diffusion}} + \underbrace{\gamma_8 log(GDPpc)_{it-1} + \gamma_9 log(GDPpcGrowth)_{it-1} + \gamma_{10} exportsGDP_{it-1} + \gamma_{11} log(population)_{it-1} + \gamma_{12} internet_{it-1}}_{\text{controls}} + \epsilon_{it}$$

Figure 26: Civil Conflict Duration Full Model Specification

Table 5 below demonstrates a Country Fixed effects model for the duration of civil violence.[47] Panel corrected standard errors are shown in parenthesis.[48] Overall, Duration has a moderate fit across six models ranging from 32% (Models 2-4) to 41% R2 (Model 1). The error is significantly higher than of Severity model's, indicative of more bias (0.66-0.7)[49].

[47] Hausman Test revealed significant difference between Fixed Effects and Random Effects coefficients, favoring the former (Prob > chi2 = 0.0000). Visit Appendix for the output.
[48] Wooldridge (2002) serial correlation test and Breusch-Pagan/ Cook–Weisberg heteroscedasticity test reveal the presence of both problems (Prob > chi2 = 0.0000). Visit Appendix for details.
[49] Given that lnduration takes values between 0-10 with a mean of 0.53 and a sd of 1.67, the RMSE of 0.7 is moderate and higher compared to the Severity model.

Endogenous-only Model 1 has the highest R2 of 41.2%, indicating that the past duration of conflict can moderately predict the current conflict duration. It has the highest bias of RMSE =0.7 among all six models. Consistent with the Severity and Onset models, the endogenous process is highly significant and positively impacts the current duration level (b = 0.187).

Exogenous Political Model 2 has a significantly lower fit of 32%. All independent variables are strongly significant. Like the severity model, democracy is the driving force among political factors. Consistent with prior literature, it is negatively associated with duration at b= -0.183 (Wucherpfennig et al. 2012). State capacity maintains consistent behavior across all three measures of violence (b= -0.143). Political repression has a positive impact on duration, though the effect is negligible (b=0.074). Despite the significant results, the predictive power of political variables is about 9% lower than endogenous autoregressive model's alone. The RMSE is comparable to Model 1 (0.7).

Socio-Economic Exogenous Model 3 shows no improvement in model performance (R2=32%, RMSE = 0.7). The results are almost identical to Model 2. Socio-economic equality variables are not relevant for the duration. Unlike the onset and the severity, gender equality has no impact on the duration of violence.

Exogenous Diffusion Model 4 shows little change compared to the previous two models. Consistent with the severity model, the adjacent conflict has no impact once the conflict is in progress. The remaining variables hold consistent results with Model 3.

VARIABLES	(1) AR(1)	(2) Poli	(3) Socio-Econ	(4) Diffusion	(5) All Controls	(6) Full
lnduration_{t-1}	0.187***					0.0883**
	(0.0424)					(0.0427)
APE_{t-1}		-0.143***	-0.137***	-0.136***	-0.0370	-0.0393
		(0.0378)	(0.0382)	(0.0380)	(0.0404)	(0.0387)
repression_{t-1}		0.0735***	0.0719***	0.0725***	0.0496*	0.0481*
		(0.0258)	(0.0256)	(0.0256)	(0.0267)	(0.0258)
democ_{t-1}		-0.183***	-0.184***	-0.182***	-0.138***	-0.125***
		(0.0381)	(0.0371)	(0.0370)	(0.0382)	(0.0362)
$\text{income equality}_{t-1}$			0.0426	0.0425	0.0639	0.0603
			(0.0542)	(0.0532)	(0.0579)	(0.0557)
$\text{gender equality}_{t-1}$			-0.101	-0.0944	-0.0749	-0.0623
			(0.0847)	(0.0821)	(0.103)	(0.102)
$\text{adjacent conflict}_{t-1}$				0.0271*	0.0273	0.0253
				(0.0161)	(0.0184)	(0.0183)
lnGDP pc_{t-1}					-0.185*	-0.150
					(0.109)	(0.0974)
$\text{lnGDP pc growth}_{t-1}$					0.00732	0.00961
					(0.0149)	(0.0148)
exports GDP_{t-1}					-0.00910	0.00170
					(0.0388)	(0.0371)
internet_{t-1}					0.0846***	0.0724***
					(0.0283)	(0.0272)
$\text{lnpopulation}_{t-1}$					-0.873***	-0.699***
					(0.215)	(0.210)
Constant	-0.0683	0.0180	0.0811	0.0674	1.950***	1.564***
	(0.209)	(0.0600)	(0.0733)	(0.0722)	(0.462)	(0.441)
Observations	4,374	4,074	4,074	4,074	3,710	3,710
R^2	0.412	0.320	0.321	0.322	0.338	0.379
RMSE	0.702	0.697	0.697	0.697	0.663	0.663
Number of Countries	162	153	153	153	149	149

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Duration of Civil Violence, Country Fixed Effects Model with PCSE

The results differ once controls are introduced in Model 5. Model performance improves slightly (R2= 34%, RMSE = 0.66). Population size becomes the most significant factor of conflict duration (b= -0.873). Its effects are approximately six times larger than democracy's (b= -0.138). Thus, a larger population size is associated with a shorter conflict duration. Political capacity's effect vanishes once the population size is accounted for. The same is true for political repression, which is consistent with Collier and Hoeffler's findings (2001). Democracy is the only political factor that holds consistent

results across all models. Among controls, internet use positively impacts the duration of the conflict, though at a negligible rate (b=0.085).

Full Model 6 has the highest R2 among the five models (38%), though slightly lower than Model 1 (vs. 41%). It has the lowest RSME (0.66) across all six models. Population size remains the largest driver of the duration (b= -0.699), followed by democracy (b=-0.125). Lag Duration is significant and positive, though the magnitude drops by half compared to Model 1 (b=0.088). Internet use behaves consistently with Model 5 (b=0.072).

Based on the results, the duration of violence significantly differs from the onset and severity. Firstly, large populations are associated with shorter violence incidents, indicative of an inverse relationship between population and duration. The opposite is true for the conflict onset (greater population size increases the probability of onset). This is quite intuitive as it takes more resources to sustain a conflict in larger-sized states. Spreading violence in smaller-sized states is more efficient as it requires fewer resources and time. A larger state is likely to suppress the violence spiraling in distant parts of the country before it grows in size. For instance, Liberia, a small West African country with a population of slightly over 5 million people, experienced a raging war from 1989 to 2004. Reversely, its neighbor, Côte d'Ivoire, which is five times Liberia's population, had much shorter domestic instability (Molemele 2015).

In addition to population size, more democratic states are less prone to protracted and severe conflicts. Neighbor violence has a tremendous effect on the onset of new violence; however, once the conflict is in progress, it has no impact on its severity or duration. Similarly, prior duration history has a negligible effect on the current violence duration.

The Frequency of Nonviolent Conflict

The fourth and last dependent variable examines low-level violence frequency. Recalling from the above, the onset, severity, and duration analyze high-level violence resulting in direct fatalities. Protest considers the instances of civil unrest that do not incur casualties. Such events are any gatherings of at least 50 people intended to make a demand to the government. Examples of such demands include labor wage disputes, opposition against police brutality, price increases or tax policies, farm issues, corruption-related demands, and social restrictions (Clark, Regan, 2015).

Examining nonviolent conflict will help identify the factors leading to its increase and potentially prevent its escalation. This section will examine nonviolent protests and compare them with violent conflict measures. Protest is measured as the number of protests occurring in a given country and year. The logarithmic transformation of protests is performed for normalization purposes. Below is a summary of the protest model using Country Fixed Effects OLS specification with PCSE.

$$\log(\text{protest})_{it} = \theta_0 + \theta_1 log(protest)_{it-1} + \underbrace{\theta_2 APE_{it-1} + \theta_3 repression_{it-1} + \theta_4 democ_{it-1}}_{\text{political}} + \underbrace{\theta_5 incomeEquality_{it-1} + \theta_6 genderEquality_{it-1}}_{\text{socio-economic}} +$$
$$\underbrace{\theta_7 adjacentConflict_{it-1}}_{\text{diffusion}} + \underbrace{\theta_8 log(GDPpc)_{it-1} + \theta_9 log(GDPpcGrowth)_{it-1} + \theta_{10} exportsGDP_{it-1} + \theta_{11} log(population)_{it-1} + \theta_{12} internet_{it-1}}_{\text{controls}} + \epsilon_{it}$$

Figure 27: Nonviolent Protest Full Model Specification

Table 6 below features Country Fixed Effects Regression results for nonviolent protest frequency.[50] Panel-corrected standard errors are shown in parentheses.[51] Protest models demonstrate better model fit than Duration models but lower than Severity models.

All endogenous processes hold consistent positive effects across four dependent variables. Endogenous-only Model 1 exhibits a moderate R2 (48.2%) and the lowest RMSE among all six models

[50] Hausman test revealed significant difference between Fixed Effects and Random Effects coefficients, favoring the former (Prob > chi2 = 0.0000). Visit Appendix for the output.

[51] Wooldridge (2002) serial correlation test and Breusch-Pagan/ Cook–Weisberg test for heteroscedasticity reveal the presence of both issues (Prob > chi2 = 0.0000). See Appendix for the output.

(0.7) 52. Past protests can moderately predict the current level based on the variable coefficient (b=0.280).

Exogenous Political Model 2 has a much lower R2 of 31.8%, indicating that political variables alone can explain roughly a third of total variation. This is significantly lower than Endogenous Model 1. Unlike violent conflict, political capacity positively impacts the nonviolent protest frequency (b=0.069). Despite such a reverse effect on protests, capacity's impact in Model 2 is negligible. The remaining political variables (repression and democracy) are insignificant.

Exogenous Socio-Economic Model 3 performs similarly (R2=31% and RMSE=0.71). However, no model variables are significant. Political capacity is irrelevant for protests once economic and gender equality is present.

Neighbor violence diffusion Model 4 remains consistent with the previous model (R2=32%). The results dramatically differ from previous conflict measures (onset, severity, and duration). No variables are significantly different from zero.

Exogenous Controls Model 5 significantly differs from the three previous models. Population size is the driving force for protests (b=1.180). However, unlike duration, it positively impacts protest frequency. This is consistent with the previous literature (Benson and Saxton 2008). In the presence of control variables, income equality is strongly significant (b=0.101), indicating that societies with greater income equality are prone to higher protest levels. Cross-border violence is associated with a slight increase in protest events (b=0.05). This is consistent with the border diffusion argument in the literature, specifically of nonviolent campaigns (Gleditsch and Rivera 2015).

VARIABLES	(1) AR(1)	(2) Poli	(3) Socio-Econ	(4) Diffusion	(5) All Controls	(6) Full
$lnprotest_{t-1}$	0.280***					0.277***
	(0.0416)					(0.0426)
APE_{t-1}		0.0692**	0.0586*	0.0596*	-0.00992	-0.00154
		(0.0308)	(0.0316)	(0.0316)	(0.0325)	(0.0265)
$repression_{t-1}$		-0.0365	-0.0386	-0.0393	-0.0442	-0.0541**
		(0.0252)	(0.0251)	(0.0251)	(0.0269)	(0.0243)
$democ_{t-1}$		0.0510	0.0442	0.0461	-0.00512	-0.0168
		(0.0414)	(0.0416)	(0.0415)	(0.0417)	(0.0333)
income $equality_{t-1}$			0.0833*	0.0844*	0.101**	0.0596
			(0.0482)	(0.0476)	(0.0503)	(0.0411)
gender $equality_{t-1}$			0.0744	0.0795	-0.124	-0.112
			(0.0601)	(0.0600)	(0.0930)	(0.0719)
adjacent $conflict_{t-1}$				0.0348*	0.0501**	0.0511**
				(0.0203)	(0.0218)	(0.0205)
lnGDP pc_{t-1}					-0.0114	0.0102
					(0.100)	(0.0803)
lnGDP pc $growth_{t-1}$					0.0109	0.00353
					(0.0144)	(0.0137)
exports GDP_{t-1}					0.0529	0.0388
					(0.0506)	(0.0398)
$internet_{t-1}$					0.0211	0.0198
					(0.0316)	(0.0255)
$lnpopulation_{t-1}$					1.180***	0.868***
					(0.260)	(0.205)
Constant	0.405	-1.063***	-1.091***	-1.112***	-3.369***	-2.493***
	(0.284)	(0.0518)	(0.0600)	(0.0603)	(0.551)	(0.449)
Observations	4,374	4,074	4,074	4,074	3,710	3,710
R^2	0.482	0.318	0.311	0.321	0.328	0.487
RMSE	0.701	0.713	0.713	0.713	0.715	0.715
Number of Countries	162	153	153	153	149	149

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Nonviolent Protest Frequency, Country Fixed Effects Model with PCSE

Full Model 6 adds endogenous effects and demonstrates the best fit across all models (R2=49%, similar to Model 1). The RMSE remains unchanged (0.71). The population is the driving force of the protest frequency (b=0.868), followed by the endogenous past protests (0.277). In the presence of endogenous protests, political repression becomes significant. It negatively impacts the protest frequency (b= -0.054). These findings fully confirm H3.[52] Diffusion of neighbor violence holds

[52] H3: Political Repression has a positive impact on conflict onset and severity, but a negative impact on protest frequency

consistent results with Model 5 (b=0.051). None of the other factors, including income equality are relevant in the full model specification.

As seen from the results, protests are largely driven by the population size, past history of protests, and instability across the border. Both duration and protest are significantly impacted by population. Contrary to violent domestic conflict, government repression can act suppressively towards low levels of violence. This suggests that repression might be an effective way to potentially suppress protests; however, once they escalate, repression can rather aggravate the conditions and increase the probability of new violence onset. This confirms Regan and Norton's findings (2005).

Similar to the previous models, low-level violence is largely an autoregressive process heavily dependent on its past history confirming prior empirical findings (Dahlum and Wig 2019). For instance, one of the former Soviet Union countries, Kyrgyzstan, has experienced several mass protest waves since its recent independence in 1991. The first major wave occurred in 2005, followed by the second one in 2010, and the last in 2020 (with multiple smaller protests in between). Perhaps the memory of past instability reinforced the future events to a certain degree.

Summary of Global Models

The results above indicate that different civil conflict dimensions require unique approaches to their prevention (Regan and Norton 2005). Viewing conflict phenomena from different angles painted a more detailed and 'broader' picture of a complex reality (Abdollahian 2021). One consistent finding across all four dependent variables is a clear path dependence as history affects future development trajectory (Midleton-Kelly 2003). This confirms H1.[53] Table 7 below summarizes all four global models with short descriptions for key variable coefficients.

[53] H1: Past history of violence positively impacts the current level of violence on onset, severity, protest and duration of conflict.

Variable Name	Onset of Violence	Log Fatalities	Log Duration	Log Protest	Comments
Lag DV	high (+) 0.718***	high (+) 0.502***	low (+) 0.0883**	medium (+) 0.277***	Significant across all
APE [1]	high (-) -0.741***	low (-) -0.0499**			Key for Onset
Repression [1]	medium (+) 0.234***		0.0481*	low (-) -0.0541**	Worsens new conflict, aids protest
Democracy [1]		low (-) -0.0611***	medium (-) -0.125***		Aids severity and duration
Adjacent Conflict [1]	medium (+) 0.337**			low (+) 0.0511**	Crucial for onset prevention
Log Population [1]	medium (+) 0.167***		high (-) -0.699***	high (+) 0.868***	Increases Onset and Protest, decreases duration
Gender Equality [1]	low (-) -0.005***	medium (-) -0.172***			Important for severity
Pseudo/ R2	0.272	0.774	0.379	0.487	Severity is best, Onset is worst
AUC/RMSE	0.851	0.418	0.663	0.715	

Table 7: Summary of the four Global Models

Though the past endogenous history has its footprint on the future, several things can be done to avoid new violence before it begins. More capable states, on average, have a lower likelihood of new onsets and will likely experience less severe violence. Thus, direct intervention to increase state capacity prior to conflict initiation is effective to mitigate future violence. However, once the violence is in progress, this approach is ineffective to prevent violence escalation. Increasing female representation in labor force is among the few levers to potentially decrease violence escalation. However, no significant policy levers can aid conflict duration. Repressive methods can slightly help to suppress low-level violence. However, once it grows violent, state coercion can potentially aggravate existing grievances and increase the probability of new violence.

Although outside of the studied sample, a recent wave of protests in Belarus (2020-2021) marked one of the most unstable times in the history of the country since its independence in 1991. The

Belarussian government received numerous criticisms of the cruel situation handling. Thousands of civilians flooded the streets of Minsk singing Tsoi's iconic song "Khochu peremen" ("I want changes"). At some point during the demonstrations, the government began releasing detainees issuing a public apology, and urging the public, "We don't need war," to avoid further escalation (Reuters 2020). Though months later, the government suppressed the protests before they escalated further.

Taking a close watch on border violence is an effective state security measure; however, given the limited resources, it is more relevant as a preventative measure of potential new violence. Once the internal conflict is initiated, states should focus on strengthening their capacity, including providing better economic conditions for women. This would positively impact the state's capacity, further pacifying potential violence severity.

Regional Models

The previous section focused on the factors influencing civil conflict, examined globally across 162 countries. It revealed valuable generalizable insights applicable to the entire sample. However, these models do not account for possible regional differences across the global sample. Unobserved geographic characteristics such as culture, mentality, prior history, or perceptions can be captured via regional study.

This subsection presents an initial exploration into the regional civil conflict heterogeneity, examining onset, severity, duration, and protest across seven geographical regions[54]. It will address research question #4[55]. Furthermore, it will serve as a starting point for generating new hypotheses regarding specific regional contexts for the future extension of this dissertation.

The remainder of this subsection is organized by the dependent variable. Each of the four dependent variables is analyzed across seven regions. Each DV follows an identical Full Model specification of endogenous and exogenous determinants of civil conflict.

The Onset of Civil Conflict

Table 8 below summarizes seven regional Pooled Probit regressions for civil conflict onset. The number of observations varies across each model, depending on the region's size. For instance, Sub-Saharan Africa is the largest area, with approximately 1000 observations, whereas South Asia is the smallest (152 observations). As known from Central Limit Theorem, models with larger sample sizes are more reliable (Rosenblatt 1956).

[54] The classification was adopted from the World Bank, with two adjustments made. First, the former Soviet Union states were separated from Europe and Central Asia, making a separate 'Former USSR' region.
Second, North America was combined together with the remainder of Europe, making its own 'Europe and North America' region.

[55] Q4: Given the above, how do these factors change across different geographic regions?

At first glance, there are significant differences between regional model results. Pseudo R2 ranges from 15.8% (Middle East & North Africa) to 33.2% (South Asia), compared to the global model's 27.2% R2. South Asia, Sub-Saharan Africa (R2=31.4%), and Latin America & the Caribbean (R2=29%) models explain the most variation among all regional models. Overall, regional models have a good classification performance. Latin American region has the highest AUC of 0.88, whereas the Middle East and North Africa have the lowest (AUC=0.78).

Recalling from the global model, endogenous past onset was the second highest variable in magnitude for onset. However, on a regional level, it is only significant in Sub-Saharan Africa, and East Asia & the Pacific. It is the most important factor increasing the onset likelihood in East Asia and the Pacific (b=0.605) and the second highest variable in magnitude in Sub-Saharan Africa (b=0.775). This is perhaps due to a long history of civil conflicts within Sub-Saharan Africa.

VARIABLES	(1) Europe & N America	(2) LA & Caribb	(3) Former USSR	(4) ME & N Africa	(5) Sub-S Africa	(6) South Asia	(7) East Asia & Pacific
$onset_{t-1}$	0.096	-0.208	0.299	0.216	0.775***	0.477*	0.605**
	(0.339)	(0.240)	(0.351)	(0.193)	(0.115)	(0.271)	(0.237)
APE_{t-1}	3.104*	-1.151	-2.169	-0.330	-1.278**	0.520	-0.904
	(1.586)	(0.974)	(1.484)	(0.880)	(0.538)	(2.007)	(1.103)
$repression_{t-1}$	-0.091	0.285**	0.587***	0.383***	0.252***	-0.348	0.143
	(0.169)	(0.130)	(0.211)	(0.112)	(0.063)	(0.255)	(0.155)
$democ_{t-1}$	-0.109*	-0.013	0.048	0.032	0.005	-0.030	0.047
	(0.065)	(0.040)	(0.042)	(0.044)	(0.018)	(0.063)	(0.041)
income $equality_{t-1}$	-0.028	-0.033	-0.007	0.054	-0.003	0.081	-0.104**
	(0.044)	(0.062)	(0.051)	(0.037)	(0.023)	(0.127)	(0.052)
gender $equality_{t-1}$	-0.017**	-0.009	-0.034**	-0.014**	-0.013***	-0.005	0.002
	(0.009)	(0.012)	(0.017)	(0.006)	(0.004)	(0.010)	(0.012)
adjacent $conflict_{t-1}$	0.364*	0.362	-0.500	0.398	0.503**		-0.025
	(0.210)	(0.246)	(0.438)	(0.418)	(0.246)		(0.349)
lnGDP pc_{t-1}	-0.197	0.139	0.185	-0.058	-0.117	1.034	-0.078
	(0.311)	(0.206)	(0.330)	(0.145)	(0.105)	(0.656)	(0.193)
lnGDP pc $growth_{t-1}$	0.004	-0.089	-0.256	0.145*	0.020	-0.438*	0.017
	(0.076)	(0.080)	(0.158)	(0.082)	(0.050)	(0.224)	(0.117)
exports GDP_{t-1}	-0.006	0.016**	-0.016	0.003	-0.005	-0.024	-0.000
	(0.010)	(0.007)	(0.010)	(0.005)	(0.005)	(0.032)	(0.004)
$internet_{t-1}$	0.001	-0.009	-0.010	0.007**	-0.009	-0.082*	-0.002
	(0.005)	(0.006)	(0.008)	(0.004)	(0.008)	(0.045)	(0.007)
$lnpopulation_{t-1}$	0.233**	0.595***	0.044	-0.103	0.312***	0.378**	0.158*
	(0.101)	(0.132)	(0.133)	(0.118)	(0.057)	(0.166)	(0.094)
Constant	-1.172	-8.260***	0.218	-1.555	-2.468**	-11.742*	-1.193
	(2.929)	(2.062)	(2.167)	(2.018)	(1.028)	(6.143)	(2.163)
Observations	818	582	339	418	1,030	152	371
AIC	217.1	277.8	152.7	335.8	802.8	157.6	233.7
Log Lik	-95.53	-125.9	-63.34	-154.9	-388.4	-66.79	-103.9
AUC	0.850	0.876	0.862	0.777	0.857	0.865	0.817
Pseudo R^2	0.217	0.291	0.247	0.158	0.314	0.332	0.195

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Civil Conflict Onset Regional Models, Pooled Probit Regression

Though state political capacity was the most considerable pacifying force in the global Onset model, it is only relevant for Sub-Saharan Africa in the regional analysis. Recalling from the EDA chapter, Sub-Saharan Africa has the lowest average political capacity across all regions. This model's APE coefficient is the highest in magnitude, significantly outperforming other endogenous and exogenous variables (b= -1.278). For instance, South Africa, whose average APE is approximately 2.5 times greater than DRC's, experienced eight times fewer onsets within 28 years (UCDP Event Dataset, 2022).

Political repression shows strong results across four different regions: Latin America & the Caribbean, the Former USSR, the Middle East & North Africa, and Sub-Saharan Africa, confirming the global model findings. These four regions have relatively lower democracy levels and higher existing

government repression.[56] Perhaps, such states have increased levels of civilian grievances due to underdeveloped institutions attributed to the regime type and high existing repression levels. Consequently, state coercion will only aggravate the existing dissatisfaction among populations and potentially increase the likelihood of new violence. The former USSR has the highest repression coefficient (b=0.587). For instance, Kyrgyzstan's former president, Kurmanbek Bakiyev, used force during the political protests against the government in 2010. This action added fuel to the existing grievances escalating the violence and resulting in a coup d'état.

Gender equality has a low negative impact on conflict onset across four regions: Europe & North America, the Former USSR, the Middle East & North Africa, and Sub-Saharan Africa, consistent with the global model.[57]

Cross-border violence diffusion is only significant in Sub-Saharan Africa, implying that it is especially prone to border conflict spillover. This is the third variable in magnitude for this region (b=0.503), half as important as the capacity. Historically, the diffusion of war is common in this region. For instance, the Sahel region in Africa is known for its "conflicts without borders" (ICRC, 2020). When internal violence in Mali escalated, armed groups multiplied and even spread to its neighboring Burkina Faso and Niger (NRC, 2019).

East Asia and the Pacific is the only region where income equality can moderately decrease the probability of conflict initiation (b= -0.104). On average, some higher-income equality states, such as Singapore, ROK, and New Zealand, have not experienced conflict onsets within the given period. However, lower-income equality states, such as Thailand, the Philippines, and Myanmar, had roughly 30% more onsets in the same timeframe (Gleditsch et al., 2002; Shawn et al., 2022).

[56] South Asia would be expected to be a part of this group, however, due to a small sample size, the results from the South Asia model are not highly reliable.

[57] Three of the four regions are developing countries with lower economic development and less democratic regimes.

The population can increase the potential onset likelihood in four different regions (1,2,5,6)[58]. The strongest effects are in Latin America (b=0.595).

Among other controls, commodity exports can increase the probability of potential onset in Latin America (b=0.016). Internet use has positive impact on onset in Middle East and North Africa (0.007). Despite the significance, both coefficients are negligibly small.

While global models helped identify general drivers of intrastate conflict onset, regional models demonstrated nuanced results across geographic areas. Endogenous past onset can increase onset likelihood across two regions (5,7), suggesting that the prior year's conflict has a heterogeneous impact across geographic areas[59]. State capacity had the highest magnitude in the global model. It is only in Sub-Saharan Africa in the regional models, serving as the largest factor that can potentially decrease the probability of potential conflict onset. Perhaps, this is due to the region's low economic development, state capacity, high repression, and underdeveloped institutions compared to other regions.

Political repression finds strong regional support across four regions. Gender equality holds a consistently minimal impact across regions. Neighbor spillover effects are region-specific for Sub-Saharan Africa only, emphasizing the complex violence history and weak state capacity in the region. Consistent with the global model, regime type plays no role in new violence initiation. Overall, regional models provided further support to the main hypotheses. They revealed conflict coping mechanisms should be tailored toward specific regional contexts.

[58] Europe & North America, Latin America & the Caribbean, Sub-Saharan Africa, and South Asia.
[59] Sub-Saharan Africa and East Asia & the Pacific.

The Severity of Civil Conflict

Table 9 below presents seven regional models for civil conflict severity. It replicates the structure and specification of the Onset model above. From the results, the Severity models better perform than the Onset ones, with the highest R2 of 90% (South Asia) and the lowest, 58% (Former USSR). Europe and North American model has the lowest bias (RMSE=0.224), whereas Sub-Saharan Africa has the highest (RMSE =0.542).

VARIABLES	(1) Europe & N America	(2) LA & Caribb	(3) Former USSR	(4) ME & N Africa	(5) Sub-S Africa	(6) South Asia	(7) East Asia & Pacific
$\ln fatalities_{t-1}$	0.237***	0.494***	0.315***	0.393***	0.490***	0.839***	0.599***
	(0.0731)	(0.0580)	(0.0741)	(0.0669)	(0.0511)	(0.0588)	(0.0627)
APE_{t-1}	0.0104	0.00373	-0.0651	0.0897	-0.159***	-0.0921	-0.0345
	(0.0308)	(0.0471)	(0.0781)	(0.0595)	(0.0506)	(0.111)	(0.0487)
$repression_{t-1}$	-0.0603**	0.0331	0.152***	0.0594	0.0260	-0.0361	0.0596
	(0.0275)	(0.0325)	(0.0464)	(0.0422)	(0.0359)	(0.0507)	(0.0500)
$democ_{t-1}$	-0.144**	-0.109	-0.193**	-0.0530	-0.0372	-0.0498	-0.0450
	(0.0640)	(0.0697)	(0.0938)	(0.108)	(0.0422)	(0.0577)	(0.0522)
$income\ equality_{t-1}$	-0.113***	-0.0815	-0.00384	0.0736	0.213***	-0.0932	0.0206
	(0.0422)	(0.108)	(0.0964)	(0.180)	(0.0752)	(0.210)	(0.0675)
$gender\ equality_{t-1}$	-0.122	-0.0226	-0.355	0.197	-0.848***	0.232	0.327
	(0.0917)	(0.142)	(0.277)	(0.232)	(0.151)	(0.286)	(0.251)
$adjacent\ conflict_{t-1}$	0.0120	-0.0334	0.0690	-0.0347*	-0.0106		0.0539
	(0.0108)	(0.0239)	(0.0655)	(0.0206)	(0.0205)		(0.0437)
$\ln GDP\ pc_{t-1}$	-0.114	-0.325	0.0539	0.118	0.296	-0.378	0.186
	(0.125)	(0.324)	(0.218)	(0.152)	(0.192)	(0.368)	(0.165)
$\ln GDP\ pc\ growth_{t-1}$	-0.00106	-0.0551***	-0.133***	0.0357	-0.0183	-0.0443	-0.00730
	(0.00977)	(0.0197)	(0.0408)	(0.0225)	(0.0169)	(0.0383)	(0.0239)
$exports\ GDP_{t-1}$	0.0363	0.0613	0.0654	-0.00832	-0.0126	0.310*	0.0928*
	(0.0435)	(0.0704)	(0.0708)	(0.0602)	(0.0762)	(0.165)	(0.0514)
$internet_{t-1}$	0.0145	0.0304	-0.0735	0.0195	0.150	0.217	-0.000629
	(0.0231)	(0.0592)	(0.0700)	(0.0509)	(0.0922)	(0.260)	(0.0495)
$\ln population_{t-1}$	-1.316	-0.0668	-0.798	-0.0731	-0.0362	0.297	-1.013
	(0.929)	(0.561)	(0.908)	(0.218)	(0.243)	(0.988)	(0.620)
Constant	2.897	-0.0249	-0.205	-0.291	-0.0745	0.0321	2.763
	(2.079)	(0.524)	(0.748)	(0.415)	(0.415)	(3.416)	(1.915)
Observations	818	582	339	418	1,030	152	371
R^2	0.700	0.757	0.575	0.783	0.740	0.903	0.879
RMSE	0.224	0.359	0.455	0.439	0.542	0.337	0.343
Number of Countries	31	23	14	18	42	6	15

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Civil Conflict Severity Regional Models, Country Fixed Effects Model with PCSE

Consistent with the global model, endogenous past fatalities are the main contributing force to the violence severity across all regions. These results confirm that limited measures are available to prevent its escalation once a conflict is in place. The current violence level is essentially the function of its past. This is especially true for Asia, where lag DVs are the only significant variables (Models 6 and 7: b=0.839, b=0.599). These results dramatically differ from the Onset regional models.

Political capacity only affects conflict severity in Sub-Saharan Africa, consistent with the onset model (b= -0.159). Thus, more capable Sub-Saharan African states are less likely to have civil conflict, and if they do, those are less likely to be severe. However, APE has the smallest impact among other variables in the Sub-Saharan African model.

Consistent with the global model, democracy has pacifying effects on conflict severity. These effects hold across two regions only: Europe & North America and the Former USSR. The former are the societies with post-materialistic values, whereas the latter are the countries recently liberated from a long reign of communism. Perhaps such significant results in the former USSR region are attributed to the Baltic states (Lithuania, Latvia, and Estonia) that have the highest democracy levels in the given region. These states experienced the least violence within their region after the USSR's collapse in 1991. Among the FSU states, Russia had the most severe violence in the given timeframe. It has a significantly lower democracy level relative to the Baltic states.

Similar to the Regional Onset model, political repression aggravates conflict in the post-Soviet countries, perhaps due to its repressive history under communist rule (b=0.152). It is negatively associated with the conflict severity in Europe and North America; however, the impact is negligible (b= -0.06).

Though insignificant in a global model, income equality can potentially pacify conflict severity in Europe and North America (b= -0.113) but aggravate it in Sub-Saharan Africa (b=0.213). This is a puzzling finding that challenges H5.[60] Further research should be done to clarify this finding.

Gender equality finds further support on a regional level, particularly in Sub-Saharan Africa. Consistent with the Onset model, it can potentially suppress violence severity and has the greatest magnitude among all other variables (b= -0.848). For instance, Rwanda is famous for its women's

[60] H5: Income and gender equality have a negative impact on conflict onset and severity.

active role in peacebuilding efforts and conflict resolution. It is among the world's top countries for women's equality.

Consistent with the global Severity model, economic development can negatively impact conflict severity. These results are substantial for the former Soviet states (b= -0.133).

Overall, regional model findings align with the global model results for the severity of violence. They demonstrate cyclical violence behavior, providing robust evidence in a regional analysis. Political repression can aggravate both new and ongoing violence in the post-Soviet region. For Sub-Saharan Africa, gender equality is one of the most effective tools to cope with conflict.

The Duration of Civil Conflict

Recalling from the global Duration model results, population and regime type had the most considerable impact on duration. Table 10 below presents seven regional conflict duration models.

The Sub-Saharan African model explains the most variation (R^2=46%), whereas the former USSR model fits poorly at 16% R^2. Consistent with the Severity, Europe and North American model has the lowest bias (RMSE = 0.184), whereas the Middle East & North Africa, and South Asia – the highest (RMSE=1.003).[61]

[61] For comparison purposes, the Global Duration Model's RMSE = 0.663.

VARIABLES	(1) Europe & N America	(2) LA & Caribb	(3) Former USSR	(4) ME & N Africa	(5) Sub-S Africa	(6) South Asia	(7) East Asia & Pacific
$lnduration_{t-1}$	-0.0555	-0.0487	0.0533	0.0852	0.0857*	-0.00746	0.190***
	(0.0847)	(0.0858)	(0.0980)	(0.0738)	(0.0505)	(0.104)	(0.0698)
APE_{t-1}	-0.00190	-0.0351	-0.0986	-0.0491	-0.0686	-0.0545	0.0939
	(0.0454)	(0.0922)	(0.0822)	(0.0848)	(0.0805)	(0.214)	(0.0947)
$repression_{t-1}$	-0.0101	0.166**	0.00260	0.0975	0.0930**	-0.209	-0.00964
	(0.0165)	(0.0744)	(0.0513)	(0.0653)	(0.0469)	(0.128)	(0.0741)
$democ_{t-1}$	-0.0684	0.124	-0.0858	-0.212	-0.140**	-0.137	-0.216**
	(0.0712)	(0.128)	(0.100)	(0.158)	(0.0664)	(0.164)	(0.0969)
income $equality_{t-1}$	0.00737	-0.0774	0.225*	-0.0812	0.00446	0.314	-0.0354
	(0.0634)	(0.421)	(0.133)	(0.263)	(0.0971)	(0.487)	(0.0851)
gender $equality_{t-1}$	0.221**	0.181	-0.213	0.490	-0.873***	0.210	-0.112
	(0.107)	(0.325)	(0.344)	(0.397)	(0.194)	(0.617)	(0.387)
adjacent $conflict_{t-1}$	0.0181**	0.0229	0.144	0.0387	0.0238		0.00266
	(0.00798)	(0.0610)	(0.101)	(0.0409)	(0.0336)		(0.0717)
$lnGDP\ pc_{t-1}$	0.745**	-1.472**	0.332	-0.264	0.187	-0.505	-0.107
	(0.336)	(0.717)	(0.238)	(0.410)	(0.197)	(0.523)	(0.334)
ld GDP pc $growth_{t-1}$	0.000560	-0.0791	-0.128**	0.0484	0.0624**	-0.192	0.0149
	(0.00708)	(0.0490)	(0.0578)	(0.0323)	(0.0295)	(0.164)	(0.0343)
exports GDP_{t-1}	-0.0964	0.342**	0.0474	0.0182	-0.0141	-0.0455	-0.134
	(0.0741)	(0.162)	(0.0697)	(0.117)	(0.110)	(0.390)	(0.0903)
$internet_{t-1}$	-0.113**	0.399**	-0.201**	0.178**	0.204	-0.0950	0.109
	(0.0534)	(0.172)	(0.101)	(0.0756)	(0.131)	(0.665)	(0.0804)
$lnpopulation_{t-1}$	-1.162	-0.750	-0.0167	-1.053**	-0.751**	-0.344	-2.067
	(1.081)	(0.795)	(0.783)	(0.440)	(0.375)	(2.394)	(1.375)
Constant	1.060	3.813**	0.275	-2.441***	-1.563**	2.702	5.831
	(2.271)	(1.532)	(0.710)	(0.896)	(0.715)	(7.993)	(4.333)
Observations	818	582	339	418	1,030	152	371
R^2	0.194	0.284	0.162	0.174	0.460	0.392	0.269
RMSE	0.184	0.496	0.621	1.003	0.589	1.003	0.589
Number of Countries	31	23	14	18	42	6	15

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Civil Conflict Duration Regional Models, Country Fixed Effects Model with PCSE

Recalling from the global duration model, population size was the most important factor for conflict duration. On a regional level, it is significant in the Middle East and North Africa (b= -1.053) and Sub-Saharan Africa (b= -0.751). For instance, the average Syrian conflict in the sample is about three times longer than the average conflict in Egypt. However, the Syrian population is approximately four times smaller than Egypt's.

Regime type only matters in Sub-Saharan Africa (b= -0.140) and East Asia & the Pacific (b=- 0.216), where more open polity regimes are associated with shorter conflicts. Most states in both regions have moderate to low democracy, especially in Sub-Saharan Africa (Polity5 Annual Time Series, 2020). For instance, Myanmar is among the least democratic states in the East Asian region[62]. On average, it had

[62] Average democracy in Myanmar is 1.00 (1991-2018).

the longest violence in the region (1991-2018). Meanwhile, its neighbor Thailand which has a much higher relative democracy[63] levels, experienced approximately 3.5 times shorter conflicts.

Though repression had no impact in the global model, it significantly positively affected conflict duration in Latin America and Sub-Saharan Africa (b=0.166, b=0.093). The effect in the latter region is relatively small.

Gender equality negatively impacts potential violence duration in Sub-Saharan Africa (b= -0.873). This is consistent with the Onset and Severity models, suggesting gender equality-oriented economic policies for Sub-Saharan Africa. These may boost political capacity, further mitigating both future and ongoing violence. On the other hand, gender equality has a reverse effect in post-materialistic European and American societies (Model 1, b=0.221). Post-materialistic societies with better political institutions, economic and political openness, and higher gender equality encourage freedom of expression. This might prolong the conflict, but not its severity (as no impact was seen in the regional Fatalities model above). In addition, economic development is positively associated with duration in this region (b=0.745).

Neighbor spillover has no substantial impact in any region. These results are consistent with the global model.

Among controls, internet use shows significant substantial effects across four regions (1,2,3,4). In Europe & North America, and the Former USSR, it has a negative impact on duration (b= -0.113, b= -0.201). However, the reverse is true for Latin America & the Caribbean, and the Middle East & North Africa (b=0.399, b=0.178).

Economic development has the most significant impact on conflict duration in Latin America (b= -1.472). Like the Severity model, economic growth has a pacifying role in conflict duration, but only

[63] Average democracy in Thailand is 5.89 (1991-2018).

for the former Soviet Union region (b= -0.128). Finally, commodity exports positively affect duration in the Latin American area (b=0.342).

South Asian region shows no significant variables despite its moderate model fit (R^2=39.2%). This may be due to a small sample and higher bias. Future studies can help clarify these findings.

The Frequency of Nonviolent Conflict

Table 11 below demonstrates the results of seven regional Country Fixed Effects regressions for Protest Frequency. Overall, the model fit (R^2) ranges between 28% (Former USSR) and 62% (Europe and North America). RMSE is the lowest (0.63) for East Asia and the Pacific and the highest (0.83) for the Former USSR.

Endogenous past protest frequency is significant in every region but South Asia.[64] The coefficients have similar magnitude across all six areas (ranging between 0.169 – 0.369). In the Middle East and North Africa, past protest number is the only significant theoretical variable, implying that the current low-level violence is primarily determined by its past.

[64] The results for South Asia are not very robust considering a small sample of 152 observations.

VARIABLES	(1) Europe & N America	(2) LA & Caribb	(3) Former USSR	(4) ME & N Africa	(5) Sub-S Africa	(6) South Asia	(7) East Asia & Pacific
$lnprotest_{t-1}$	0.227***	0.169***	0.247***	0.328***	0.226***	-0.0271	0.369***
	(0.0553)	(0.0588)	(0.0702)	(0.0713)	(0.0484)	(0.0993)	(0.0635)
APE_{t-1}	0.0552	-0.141**	0.273**	-0.00416	-0.0790	-0.216	-0.0446
	(0.114)	(0.0602)	(0.111)	(0.0862)	(0.0557)	(0.164)	(0.0971)
$repression_{t-1}$	-0.133**	-0.0986	-0.0128	-0.0119	-0.0920**	-0.0206	0.0303
	(0.0660)	(0.0642)	(0.0849)	(0.0656)	(0.0360)	(0.102)	(0.0778)
$democ_{t-1}$	-0.327**	0.0441	0.0325	0.302*	0.0411	-0.0189	-0.179**
	(0.131)	(0.0787)	(0.131)	(0.166)	(0.0537)	(0.108)	(0.0837)
income $equality_{t-1}$	0.273**	-0.0846	0.212*	-0.109	0.145*	-0.522	0.117
	(0.132)	(0.198)	(0.114)	(0.250)	(0.0758)	(0.354)	(0.117)
gender $equality_{t-1}$	0.526***	0.0815	-0.248	0.276	-0.208	-0.187	0.546
	(0.169)	(0.177)	(0.465)	(0.365)	(0.131)	(0.437)	(0.389)
adjacent $conflict_{t-1}$	0.162***	-0.0417	0.189	-0.0671	-0.0462		0.104*
	(0.0381)	(0.0449)	(0.150)	(0.0572)	(0.0398)		(0.0547)
$lnGDP\ pc_{t-1}$	0.970***	-0.982**	-0.498**	0.416	0.562***	-1.015*	0.731**
	(0.346)	(0.473)	(0.247)	(0.287)	(0.162)	(0.557)	(0.318)
lnGDP pc $growth_{t-1}$	-0.0139	0.0157	0.0216	0.0322	0.00837	-0.0368	-0.0116
	(0.0304)	(0.0278)	(0.0635)	(0.0303)	(0.0254)	(0.0939)	(0.0505)
exports GDP_{t-1}	-0.165**	-0.0185	0.0386	0.0924	-0.270***	0.430	0.165*
	(0.0715)	(0.116)	(0.108)	(0.106)	(0.0846)	(0.323)	(0.0842)
$internet_{t-1}$	-0.00976	-0.0277	-0.0432	0.184**	-0.175*	0.276	-0.0549
	(0.0580)	(0.0980)	(0.0770)	(0.0933)	(0.103)	(0.487)	(0.0920)
$lnpopulation_{t-1}$	-1.239	0.637	-0.401	-0.234	1.158***	4.152**	-0.369
	(1.050)	(0.603)	(1.337)	(0.560)	(0.295)	(1.619)	(1.204)
Constant	0.278	1.202	0.0601	-1.064	1.652***	-11.64**	1.590
	(2.480)	(0.801)	(0.972)	(1.056)	(0.576)	(5.406)	(3.722)
Observations	818	582	339	418	1,030	152	371
R^2	0.620	0.399	0.280	0.464	0.374	0.534	0.611
RMSE	0.691	0.678	0.828	0.648	0.735	0.706	0.629
Number of Countries	31	23	14	18	42	6	15

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Nonviolent Protest Frequency Regional Models, Country Fixed Effects Model with PCSE

Recalling from the global protest model, population size strongly impacted protest frequency. Regional models reveal such effects in two regions only, namely South Asia (b=4.152) and Sub-Saharan Africa (b=1.158). The impact is substantial, especially in South Asia, where it is the only significant predictor of protests.[65]

While repression generally aggravates existing severe conflict, it has a pacifying effect on low-level violence. Regional findings indicate that these effects are only present in Europe & North America (b= -0.133). Given higher levels of development, more advanced institutions, and larger equality, such states are expected to have higher satisfaction levels. Perhaps, that is the reason why coercion would not fuel more grievances and could rather pacify nonviolent protests in Western societies as opposed to other regions.

[65] Given the limited sample size, these results may not be as reliable and future studies might shed more light.

Even though democracy does not generally affect protests (global model), regional models show otherwise. It is inversely related to protest frequency in Europe & North America (b= -0.327) and East Asia & the Pacific (b= -0.179). Contrary to initial assumptions, democratic regimes are not associated with an increased frequency of protests.

The regional protest model reveals that income equality may positively affect nonviolent protests (Europe & North America, b=0.273).[66] Higher income equality societies have more resources in people's hands. Perhaps, the latter can serve as additional means to mobilize potential protests.[67]

Gender equality has positive effects on protest frequency in Europe and North America. Unlike the violent conflict models, where gender equality played the most significant role in Sub-Saharan Africa, it has the opposite effect in highly developed societies. Protests short of violence are more abundant in communities with a more extensive female economic representation. The effects are significantly high (approximately twice the size of income equality, b=0.526). These results are consistent with the regional duration model for Europe and North America.

Unlike the severity and duration models, diffusion effects of high-level violence can potentially increase protest frequency in post-materialistic European societies, as seen in the results (b=0.162).

Puzzling results related to Political capacity are found in Latin American and post-Soviet regions. APE is significant and has a negative impact on protest frequency in Latin America; however, positive in the post-Soviet Space. As the former communist regime, former USSR countries have little history of protests. Higher capacity states in that region belong to Baltic European states, with more advanced intuitions and more pronounced freedom of expression. Perhaps, that is the reason why capacity rather positively impacts the protest frequency in this region.

[66] This region has the highest average income equality level among all regions.
[67] As a side note, income equality had no impact on violent conflict.

Among controls, economic development is the largest variable in magnitude significant in five regions (1,2,3,5,7). In Europe & North America, it is the most important positive driving factor of protests. Developed economies such as the UK and Germany have experienced many protests throughout the given period. These include anti-refugee demonstrations in Germany in 2016 and the Right2Water protests in Ireland in 2014. A similar relationship holds for Sub-Saharan Africa, East Asia & the Pacific. The reverse is true for Latin America and the Former USSR.

Overall, regional model results align with the global model findings. The history of protests matters across regions. Even though the population was the most significant driver of protests in the global model, it is only relevant in two areas (5,6). Instead, economic development and political factors (capacity, repression, democracy) consistently matter across multiple regions. Perhaps the most interesting regional finding concerns gender equality. It showed adverse effects on violent conflict in Sub-Saharan Africa but a positive impact on nonviolent protest in Europe and North America.

The next chapter will conclude this dissertation by summarizing key findings, providing policy implications, and stating final remarks based on these findings.

Chapter VI. Conclusion

This dissertation has aimed to identify structural determinants of intrastate violence to prevent it at different stages, including before its initiation and once it is in progress. To provide effective policy recommendations, civil conflict was examined from different angles, including its onset, duration, severity, and frequency. The results have mostly aligned with the initially proposed hypotheses; however, several nuances were discovered during the analysis. First, different conflict measures reveal specific approaches to dealing with conflict at varying stages. Secondly, the 'one size fits all' framework does not hold across different geographic regions requiring a unique approach toward each area. Econometric analysis was used to help answer these questions by leveraging the data- perhaps one of the most potent tools once referred to as 'the new oil' (Humby, 2006).

Summary of the Results

Table 12 below is a master table summarizing global and regional model results for each dependent variable. It is constructed to easily compare each dependent variable across eight models (global + 7 regional). The summaries are based on the Full model specifications from the Results chapter. The main independent variable effects on each DV are qualitatively described based on sign and magnitude (low, medium, high).[68] Second column in the table presents global model findings across each DV, followed by the seven regional models from the subsection above.

The Global model column shows substantially different results across the four conflict measures. Lag DV is the only significant variable for all four DVs, indicating the significance of historicity in each model. However, the effect is low for conflict duration. Political capacity has the most substantial

[68] Coefficient magnitude from the Final models in the Results chapter was converted into a qualitative scale (low, medium, high) based on approximation. Population is the only control variable included in the summary due to its significant impact on duration and protest.

negative impact on a potential onset and a low negative impact on severity. State repression can moderately increase the probability of onset but weakly pacify nonviolent conflict frequency. Neighbor violence has a moderate to low positive effect on the onset and protests correspondingly. Regional models revealed significantly different results across all regions; however, generally consistent results with the global model.

Civil conflict onset is mainly determined by past onset, repression, and population size. Repression shows consistent and significant positive impact across four different regions (2-5).[69] Population size has a significant effect across four regions (1,2,5,6).[70] APE and neighbor violence are only relevant in Sub-Saharan Africa. Gender equality is significant across four regions, yet at a much lower magnitude (1,3-5).[71]

Civil conflict severity is mainly a function of its past violence levels. These results are consistent across every region. Political capacity and gender equality have pacifying effects only in Sub-Saharan Africa, emphasizing its importance for policy making. Democracy has moderate adverse effects on violence severity in the former USSR (including Baltic states) and Europe & North America.

Unlike the two previous DVs, conflict duration is primarily impacted by population size and somewhat by regime type. The current conflict duration is not related to the past year's duration (lag DV is not significant). Similar to severity, gender equality has pacifying effects on the conflict longevity in Sub-Saharan Africa but has an inverse impact in post-materialistic societies (Europe and North America). Regional analysis reveals that population effects are present only in the Middle East and all of Africa, where smaller states are associated with more extended conflicts. Democracy can potentially reduce violence duration in Sub-Saharan Africa and East Asia & the Pacific.

[69] LA and the Caribbean, Former USSR, ME and North Africa, Sub-Saharan Africa
[70] Europe and North America, LA and the Caribbean, SS Africa, South Asia
[71] Europe and North America, Former USSR, ME and North Africa, Sub-Saharan Africa.

Based on the results, the past level of protests and population size determine current protest frequency. Endogenous protest effects are substantially present in all regions but South Asia.[72] In Sub-Saharan Africa and South Asia, societies with larger populations are more prone to increased frequency of protests. Additionally, state capacity has diverging impact on protests in Latin America and the former USSR regions (negative and positive correspondingly). Government repression can help pacify protests frequency, especially in Europe & North America, and somewhat in Sub-Saharan Africa. Moreover, states with higher democracy are associated with lower protest levels in region 1. Unlike in the global model, income, and gender equality are associated with increased protest frequency in Europe and North America.

[72] South Asia has a limited sample size, thus might not yield the most reliable results.

ONSET								
VARIABLES	GLOBAL	Europe & North America	LA & Caribbean	Former USSR	ME & North Africa	Sub-Saharan Africa	South Asia	East Asia & the Pacific
$onset_{t-1}$	high (+)					high (+)		high (+)
APE_{t-1}	high (-)					high (-)		
$repression_{t-1}$	medium (+)		medium (+)	high (+)	medium (+)	medium (+)		
$democracy_{t-1}$								
$income\ equality_{t-1}$								medium (-)
$gender\ equality_{t-1}$	low (-)	low (-)		low (-)	low (-)	low (-)		
$adjacent\ conflict_{t-1}$	medium (+)					medium (+)		
$population_{t-1}$	medium (+)	medium (+)	high (+)			medium (+)	medium (+)	
SEVERITY								
$severity_{t-1}$	high (+)	medium (+)	high (+)	medium (+)	medium (+)	high (+)	high (+)	high (+)
APE_{t-1}	low (-)					medium (-)		
$repression_{t-1}$		low (-)		medium (+)				
$democracy_{t-1}$	low (-)	medium (-)		medium (-)				
$income\ equality_{t-1}$		medium (-)				medium (+)		
$gender\ equality_{t-1}$	medium (-)					highest (-)		
$adjacent\ conflict_{t-1}$								
$population_{t-1}$								
DURATION								
$duration_{t-1}$	low (+)							medium (+)
APE_{t-1}								
$repression_{t-1}$			medium (+)			low (+)		
$democracy_{t-1}$	medium (-)					medium (-)		medium (-)
$income\ equality_{t-1}$								
$gender\ equality_{t-1}$		medium (+)				high (-)		
$adjacent\ conflict_{t-1}$		low (+)						
$population_{t-1}$	high (-)				high (-)	high (-)		
PROTEST								
$protest_{t-1}$	medium (+)	medium (+)	medium (+)	medium (+)	medium (+)	medium (+)		medium (+)
APE_{t-1}			medium (-)	medium (+)				
$repression_{t-1}$	low (-)	medium (-)				low (-)		
$democracy_{t-1}$		medium (-)						medium (-)
$income\ equality_{t-1}$		medium (+)						
$gender\ equality_{t-1}$		high (+)						
$adjacent\ conflict_{t-1}$	low (+)	medium (+)						
$population_{t-1}$	high (+)					high (+)	highest (+)	

Table 12: Master Summary Table of Regional and Global Models

Hypotheses Revisited

The initially proposed hypotheses essentially find support in both global and regional model results. Global model findings suggest that past conflict is associated with increased current conflict onset, severity, duration, and nonviolent conflict, confirming H1.[73] Additionally, H1 finds full support in regional analysis for the severity and protests and partial support for onset and duration.

H2 finds partial support, as political capacity has a strong negative impact on the onset and a weak effect on the severity of the conflict.[74] However, neither duration nor protests find support in the global analysis.

Findings somewhat support H3, where political repression positively impacts potential conflict onset and has a weakly negative impact on protest frequency. The results find no effect on conflict severity.[75]

Contrary to what was expected, H4 finds little support as democracy is negatively associated with violence duration but not onset or severity.[76]

Gender equality has a low to moderate negative impact on the violence onset and severity, confirming part of H5.[77] Regional study sheds more light and reveals gender equality's substantial impact on both the severity and duration in Sub-Saharan Africa; however its positive impact on protest frequency in Europe and North America.

Finally, H6 finds partial evidence from the results showing neighbor violence diffusion effects on the onset and protest only, but not on severity or duration.[78]

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[73] H1: Prioir history of violence positively impacts the current level of conflict onset, severity, protest, and duration.
[74] H2: Political Capacity has a negative impact on the onset, severity and duration of conflict.
[75] H3: Political Repression has a positive impact on conflict onset and severity, but a negative impact on protest frequency.
[76] H4: Democracy has a negative impact on conflict onset, duration and severity, but a positive impact on protest frequency.
[77] H5: Income and gender equality have a negative impact on conflict onset and severity.
[78] H6: Adjacent conflict positively impacts conflict onset, severity, and protest frequency, but not the duration.

Policy Recommendations

The key takeaway from all model results is the importance of state resource allocation toward conflict prevention before its initiation. States should focus on strengthening state capacity and addressing the population's needs in advance before any violence takes place. Methods to potentially increase civilian satisfaction, such as providing females equal access to economic resources, will benefit states in the long run. Moreover, the international community can help build capacity via foreign aid. Governments should not use coercion and repressive practices to cope with conflict as this could exacerbate existing grievances and increase the probability of violence occurrence. Additionally, governments should enforce strict border control and monitor neighbor violence to avoid potential conflict spillover. This is especially relevant for Sub-Saharan Africa.

Conflict severity reinforces itself, as past violence significantly impacts future violence. Therefore, policy levers are limited once the violence is in progress and casualties incur. Based on the global model results, a 2.8 unit increase in the past log fatalities is associated with a 140% increase in the current log fatalities, which is roughly comparable to the differences in the average fatalities levels between Ethiopia (4,494) and Sudan (6,075).[79] This is a very significant difference of 1,581 fatalities per year. Thus, forcing a truce and ending violence are the most necessary steps in preventing the violence from escalating. This may require international community's help to negotiate the conflict resolution and ceasefire terms. Increasing female representation in labor force is the lever to mitigate battle conflict escalation, particularly in Sub-Saharan Africa. For instance, a 21% increase in gender equality is associated with a 48% decrease in log fatalities, which is equivalent to the difference between the average casualty levels in Ukraine (268) and Kyrgyzstan (24), or about 244 casualties per year.[80]

[79] This example is based on the Table 4 from the Results Chapter. Standardized coefficients for $lnfatalities_{t-1}$ are converted into the actual values (2.8*0.502=1.4=> 140%). The average fatalities values for Ethiopia and Sudan are presented across the 28-year sample (1991-2018).

[80] Similarly, gender equality standardized coefficient is converted into the actual value increase for lnfatalities (-0.172* 2.8=-0.48 => -48%). 21% gender equality = 1 sd (gender equality).

One of the ways of building state capacity is via foreign aid. Governments with limited capacity can potentially increase internal government power with the help of the international community to prevent future violence. For instance, Afghanistan has a long history of internal violence rooted back to the Cold War era. With multiple instabilities during and after the communist rule, the Taliban officially emerged around 1995. The following years involve internal instability against the Taliban and Al-Qaeda and the support of the Western community via aid and troops, particularly towards the second decade of the XXI century. Eventually, the Afghanistan mission turns unsuccessful with the prevailing Taliban rule. According to the results, capacity building during ongoing violence is ineffective to prevent conflict escalation. Thus, had the US and the international community provided more support prior to the Taliban's emergence and escalation of internal instability, it might have prevented the conflict escalation.

Like severity, even less can be done to reduce the ongoing violence duration. However, certain conditions favor protracted conflict. Less democratic states with smaller populations are more prone to sustained violence. For instance, a 1.6 unit increase in log population (which is equivalent to a population size difference between Mexico and Afghanistan) is associated with a 120% decrease in log duration, which is comparable to an average civil conflict duration between Russia (238 days) and the US (0 days).[81]

Hence, countries with such characteristics should prioritize capacity building prior to conflict initiation. The US involvement in Ukraine can be considered as increasing its state's capacity to combat violence. Ukraine had a series of internal instabilities following its independence in 1991. Perhaps the

[81] Mexico's average population across the sample is 105mln, AFG – 25mln.
Standardized lnpopulation coefficient was from Table 5 was converted into the original value (-0.699*1.7*= -1.118 => -120%). The average conflict duration days for Russia and the US are estimated based on the 28-year sample.

most notable is the Orange Revolution in 2004, later followed by the Euromaidan in 2013.[82] At this time, the West did not interfere with Ukraine's internal matters. Based on the results, the most effective time for external involvement/ aid would have been before any serious conflict occurred. The events happening after 2021 (outside of the studied sample) can be considered interstate warfare with the elements of intrastate war.[83] The US and the Western allies finally interfere in the Ukrainian crisis starting in 2022 providing financial and military assistance. However, based on the current results, war-torn Ukraine's state capacity is at its lowest, where foreign aid would only marginally improve the situation. Thus, such intervention at later stages of war would not significantly aid its escalation or duration. At this stage, the international community should come up with a truce and force to end the fight. Additionally, Ukraine should prioritize increasing female economic participation to help build capacity.

Finally, nonviolent protest handling requires a different policy approach. Populous states with a history of low-level violence are more prone to increased protests. The presence of cross-border violence can potentially increase the frequency of domestic protests. Therefore, governments should allocate resources to border control. Contrary to severe conflict, political repression can serve as a pacifying force for nonviolent conflict. However, coercion should be exercised with caution. Once nonviolent protests escalate into higher forms of violence, repression can contribute to its escalation by fueling grievances and giving rise to new violent conflict. For instance, the last 2020 coup attempt in Kyrgyzstan resulted in a power transition. With a prior history of instabilities, a new protest wave did not surprise the Kyrgyz population. When the new government emerged, it used slight coercion to pacify existing unrest, ending the violence and not letting it escalate. In the following year, its

[82] Orange Revolution presents a power transition between the opposition leader Viktor Yushchenko and the pro-Russian leader Viktor Yanukovich. Euromaidan marks massive instability against the government's decision not to sign an association with EU, in other words an anti-Russia movement.

[83] Even though the current war in Ukraine is often viewed as a proxy war between Russia and the West, for the purposes of this analysis it can be considered as an internal conflict between pro-Russian and pro-Western forces.

neighbor Kazakhstan experienced internal unrest. Perhaps it should have been more alert about its neighbor's violence to avoid potential spillover.

Regional analysis revealed heterogeneous results across different geographic areas. Specifically, Europe & North America, and Sub-Saharan Africa stand out in the results compared to other regions. For instance, gender equality is an effective conflict-coping mechanism in Sub-Saharan Africa for both duration and severity. On the other hand, higher female economic equality can spark more protests in post-materialistic Western societies. These findings indicate that policymakers should adjust approaches based on specific regional contexts.

Implications

Several policy implications follow from the analysis above. First, civil conflict is a complex phenomenon that requires a multi-angled approach and separate policies depending on the type of violence and the stage of its progression. Looking at a single side of violence, such as its initiation, and not considering its severity and duration will not reveal a whole story and will not deem effective in real-life situations. Additionally, while generalizable theories of studying civil conflict are essential, International Studies scholars should be weary of adopting a single framework across different regional contexts. Tailored approaches with the consideration of unique local social contexts would be more useful for practical purposes.

Limitations and Extensions

One of the biggest arguments in civil war studies is the proper measurement of civil conflict. While the data source is a more difficult factor to manage, coming up with a particular way of defining intrastate conflict is manageable and often disputed. This dissertation comes up with a non-restrictive measure of civil conflict onset, where no requirement on civilian casualties has been imposed for it to

be considered a new onset. Such an approach may have its shortcoming by including even minor instances of internal conflict.

Prior literature often debates over the ethnic and religious components when studying civil war. In the next stage of this analysis, incorporating ethnolinguistic fractionalization and religious measures might add value. Moreover, adding more granular socio-demographic controls such as male education and employment might be useful.

The modeling section of this dissertation adopted more parsimonious models, such as simple Pooled Probit and Dynamic Fixed Effects OLS regressions. Future studies can leverage more sophisticated tools such as GMM and the latest Machine Learning methods to see whether they can outperform the traditional econometric models. The latter is beneficial for predictive purposes. Moreover, the sample size can be extended beyond 2018 once the data becomes available. Additionally, the exploratory data analysis revealed nonlinear effects between the variables. Exploring interactive and quadratic specifications (democracy) might yield useful insights.

Considering a high degree of correlation between the first three dependent variables, namely the Onset, Severity, and Duration of civil violence, setting up the study as a system of equations for all 3 DVs would be a more helpful way to study severe conflict.

For further detailed exploration, a specific region or country-level analysis can be used to test the main propositions from this dissertation. If so, the next step would be a case study of the Former Soviet Union region, given the origins of this dissertation's author. Since FSU is an understudied region, it would make a unique contribution to the field of International Relations.

Contribution to the Field

Although this dissertation has not solved civil conflict nor created its novel measures, it examined this complex phenomenon from various angles. It provided a holistic view, considering both endogenous

and exogenous factors. This work has refuted some significant previous theoretical and empirical developments in the field by synthesizing the literature and augmenting it into a multi-disciplinary framework. As highlighted above, greed-based and grievance-based factors dominated the civil war literature, generating the most robust variables in the field. While these factors find partial support in this dissertation, they omit the importance of endogenous processes in future conflict history and do not provide a comprehensive approach to studying conflict. Additionally, this research has demonstrated regional differences in civil conflict, emphasizing its importance for policy making. Trying to fit one solution across different regions will not yield effective results. Finally, it revealed unique effects of gender equality that are often omitted in structural level analysis, finding its unique role in conflict mitigation, especially in the regional context.

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Appendix

Region	Country
Europe & North America	Albania
	Austria
	Belgium
	Bosnia and Herzegovina
	Bulgaria
	Canada
	Croatia
	Cyprus
	Czech Republic
	Denmark
	Finland
	France
	Germany
	Greece
	Hungary
	Iceland
	Ireland
	Italy
	Luxembourg
	Netherlands
	North Macedonia
	Norway
	Poland
	Portugal
	Romania
	Slovak Republic
	Slovenia
	Spain
	Sweden
	Switzerland
	Turkey
	United Kingdom
	United States
Sub-Saharan Africa	Angola
	Benin
	Botswana
	Burkina Faso
	Burundi
	Cabo Verde
	Cameroon
	Central African Republic
	Chad
	Comoros
	Congo, Dem. Rep.
	Congo, Rep.
	Cote d'Ivoire
	Equatorial Guinea
	Eritrea
	Eswatini
	Ethiopia
	Gabon
	Gambia, The
	Ghana
	Guinea
	Guinea-Bissau
	Kenya
	Lesotho
	Liberia
	Madagascar
	Malawi
	Mali
	Mauritania
	Mauritius
	Mozambique
	Namibia
	Niger

Region	Country
East Asia & Pacific	Myanmar
	Indonesia
	Philippines
	Cambodia
	Papua New Guinea
	Lao PDR
	Thailand
	Malaysia
	China
	Korea, Rep.
	Japan
	Mongolia
	Singapore
	Vietnam
	Australia
	New Zealand
Former USSR	Armenia
	Azerbaijan
	Belarus
	Estonia
	Georgia
	Kazakhstan
	Kyrgyz Republic
	Latvia
	Lithuania
	Moldova
	Russian Federation
	Tajikistan
	Turkmenistan
	Ukraine
	Uzbekistan
Latin America & Caribbean	Argentina
	Belize
	Bolivia
	Brazil
	Chile
	Colombia
	Costa Rica
	Cuba
	Dominican Republic
	Ecuador
	El Salvador
	Guatemala
	Guyana
	Haiti
	Honduras
	Jamaica
	Mexico
	Nicaragua
	Panama
	Paraguay
	Peru
	Suriname
	Trinidad and Tobago
	Uruguay
	Venezuela, RB
Middle East & North Africa	Algeria
	Bahrain
	Djibouti
	Egypt, Arab Rep.
	Iran, Islamic Rep.
	Iraq
	Israel
	Jordan
	Kuwait
	Lebanon

Nigeria		Libya
Rwanda		Malta
Senegal		Morocco
Sierra Leone		Oman
Somalia		Qatar
South Africa		Saudi Arabia
Sudan		Syrian Arab Republic
Tanzania		Tunisia
Togo		United Arab Emirates
Uganda		Yemen, Rep.
Zambia	South Asia	Afghanistan
Zimbabwe		Bangladesh
		Bhutan
		India
		Maldives
		Nepal
		Pakistan
		Sri Lanka

Figure i: Countries by Region

Institutionalized Democracy Variable Coding, Polity5

Authority Coding	**Scale Weight**
Competitiveness of Executive Recruitment (XRCOMP):	
(3) Election	+2
(2) Transitional	+1
Openness of Executive Recruitment (XROPEN):	
only if XRCOMP is Election (3) or Transitional (2)	
(3) Dual/election	+1
(4) Election	+1
Constraint on Chief Executive (XCONST):	
(7) Executive parity or subordination	+4
(6) Intermediate category	+3
(5) Substantial limitations	+2
(4) Intermediate category	+1
Competitiveness of Political Participation (PARCOMP):	
(5) Competitive	+3
(4) Transitional	+2
(3) Factional	+1

Figure ii: Democracy Coding, Polity5

Civil Conflict Severity Global Model

	Coefficients (b) fixed6	(B) .	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
laglndeaths	.5205661	.7558687	-.2353026	.0109678
lagape	-.7314008	-.466687	-.2647138	.3079205
lagpts	.1288417	.1817949	-.0529532	.0254624
lagdemoc	-.0352951	.0072819	-.042577	.0141101
lagbottom50	.0215219	.0052526	.0162692	.0163074
laglaborfo~e	-.0103102	-.0041504	-.0061599	.0065617
lagadjacen~t	.0387513	.0731832	-.0344319	.0673144
lagloggdppc	-.0094207	-.0712775	.0618568	.1219972
lagloggdpp~h	-.0343523	-.0158372	-.0185151	.0123065
lagexports~p	.005977	.0013055	.0046715	.0021902
laginternet	.0009241	.0006608	.0002633	.0011304
laglogpop_th	-.0574272	.1231126	-.1805399	.1808759

b = Consistent under H0 and Ha; obtained from **xtreg**.
B = Inconsistent under Ha, efficient under H0; obtained from **xtreg**.

Test of H0: Difference in coefficients not systematic

chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 511.80
Prob > chi2 = 0.0000

Figure iii: Hausman Test for Fixed and Random Effects

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     148) =    274.513
           Prob > F =      0.0000
```

Figure iv: Serial Correlation Test results for Fatalities global model

```
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of z2lndeaths

H0: Constant variance

    chi2(1) = 514.08
Prob > chi2 = 0.0000
```

Figure v: Heteroscedasticity Test results for Fatalities global model

Civil Conflict Duration Global Model

```
. hausman fixedd ., sigmamore

                ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |    fixedd           .          Difference       Std. err.
-------------+------------------------------------------------------------
laglndurat~n |     .094419      .293147       -.198728        .0077524
      lagape |    -.3331521    -1.349319        1.016167        .2937831
      lagpts |     .0973985     .1682514       -.0708529        .0250766
    lagdemoc |    -.0337636     .0095387       -.0433023        .0135629
 lagbottom50 |     .0246417     .0076832        .0169585        .0156383
laglaborfo~e |    -.0007392    -.0019507        .0012115        .0062936
lagadjacen~t |     .0777904    -.0228515        .1006419        .0645853
 lagloggdppc |    -.1875275     -.053046       -.1344815        .1166907
lagloggdpp~h |     .031155     -.0164468        .0476018        .0117418
lagexports~p |     .000606      .0008623       -.0002562        .0020985
 laginternet |     .0028502     .001758         .0010922        .0010856
laglogpop_th |    -.3878902     .0950858       -.482976         .174467
------------------------------------------------------------------------------
                           b = Consistent under H0 and Ha; obtained from xtreg.
            B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

   chi2(12) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 689.25
Prob > chi2 = 0.0000
```

Figure vi: Hausman Test for Fixed and Random Effects

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     148) =    188.348
           Prob > F =      0.0000
```

Figure vii: Serial Correlation Test results for Duration global model

```
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of z2lnduration

H0: Constant variance

    chi2(1) = 4293.13
Prob > chi2 =  0.0000
```

Figure viii: Heteroscedasticity Test results for Duration global model

```
. hausman fixedp1 ., sigmamore

                 ---- Coefficients ----
                 |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
                 |   fixedp1         .          Difference       Std. err.
-----------------+------------------------------------------------------------
     z2lagape    |  -.0063807      .006195      -.0125757        .0157236
     z2lagpts    |  -.0382811     .0023018      -.0405829        .0074788
   z2lagdemoc    |  -.0106769     .0630172      -.0736941        .0190716
z2lagbott~50     |   .0597866      .005793       .0539936         .030892
z2laglabor~e     |  -.0112055     .0267105       -.037916        .0739126
z2lagadjac~t     |   .0426267      .051822      -.0091952        .0078814
z2lagloggd~c     |   .0983308    -.0034213        .101752        .0751842
z2lagloggd~h     |  -.0113198    -.0117398          .00042       .0028899
z2lagexpor~p     |   .0402567     .0353958       .0048609        .0212142
z2laginter~t     |   .0006784     .0214381      -.0207597        .0135217
z2laglogpo~h     |    .589535     .4157201       .1738149        .1673635
------------------------------------------------------------------------------
                           b = Consistent under H0 and Ha; obtained from xtreg.
            B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

   chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            =  82.67
Prob > chi2 = 0.0000
```

Figure ix: Hausman Test for Fixed and Random Effects

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,     148) =    366.996
           Prob > F =      0.0000
```

Figure x: Serial Correlation Test results for Protest global model

```
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of z2lnprotest

H0: Constant variance

    chi2(1) = 150.16
Prob > chi2 = 0.0000
```

```
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of z2lnprotest

H0: Constant variance

    chi2(1) = 150.16
Prob > chi2 = 0.0000
```

Figure xi: Heteroscedasticity Test results for Protest global model

Variable	VIF	1/VIF
z2lagloggd~c	3.32	0.301508
z2lagape	2.19	0.455856
z2lagpts	2.13	0.468678
z2laginter~t	1.97	0.506607
z2laglogpo~h	1.71	0.583197
z2lagexpor~p	1.67	0.598741
z2lagdemoc	1.66	0.601676
z2lagbott~50	1.63	0.614700
z2laglabor~e	1.37	0.728357
z2lagadjac~t	1.32	0.759698
z2laglnpro~t	1.17	0.852374
z2lagloggd~h	1.06	0.946281
Mean VIF	1.77	

Figure xii: VIF diagnostics

VARIABLES	(1) onset	(2) onset
$onset_{t-1}$		0.717***
		(0.072)
$lnprotest_{t-1}$	-0.024	-0.021
	(0.035)	(0.035)
APE_{t-1}	-1.010***	-0.740***
	(0.264)	(0.275)
$repression_{t-1}$	0.312***	0.236***
	(0.038)	(0.039)
$democ_{t-1}$	0.009	0.004
	(0.009)	(0.010)
income $equality_{t-1}$	-0.007	-0.009
	(0.010)	(0.009)
gender $equality_{t-1}$	-0.007***	-0.005***
	(0.001)	(0.001)
adjacent $conflict_{t-1}$	0.382***	0.339***
	(0.097)	(0.097)
lnGDP pc_{t-1}	-0.224***	-0.192***
	(0.046)	(0.047)
lnGDP pc $growth_{t-1}$	-0.047	-0.041
	(0.030)	(0.030)
exports GDP_{t-1}	-0.001	-0.001
	(0.002)	(0.002)
$internet_{t-1}$	0.003	0.003
	(0.002)	(0.002)
$lnpopulation_{t-1}$	0.193***	0.170***
	(0.026)	(0.026)
Constant	-1.151**	-1.289***
	(0.471)	(0.473)
Observations	3,710	3,710
AIC	2295	2200
Log Lik	-1135	-1086

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure xiii: Pooled Onset model with lag Protest

VARIABLES	(1) lnduration	(2) lnduration
$lnduration_{t-1}$		0.0783*
		(0.0430)
$lnfatalities_{t-1}$	0.0704**	0.0577*
	(0.0355)	(0.0332)
APE_{t-1}	-0.0247	-0.0296
	(0.0404)	(0.0389)
$repression_{t-1}$	0.0264	0.0266
	(0.0241)	(0.0238)
$democ_{t-1}$	-0.133***	-0.122***
	(0.0374)	(0.0362)
income $equality_{t-1}$	0.0491	0.0506
	(0.0568)	(0.0553)
gender $equality_{t-1}$	-0.0865	-0.0679
	(0.107)	(0.105)
adjacent $conflict_{t-1}$	0.0259	0.0244
	(0.0185)	(0.0184)
lnGDP pc_{t-1}	-0.150	-0.128
	(0.105)	(0.0972)
lnGDP pc $growth_{t-1}$	0.00985	0.0116
	(0.0149)	(0.0148)
exports GDP_{t-1}	-0.00637	0.000709
	(0.0395)	(0.0380)
$internet_{t-1}$	0.0843***	0.0721***
	(0.0288)	(0.0276)
$lnpopulation_{t-1}$	-0.830***	-0.686***
	(0.210)	(0.208)
Constant	1.838***	1.517***
	(0.461)	(0.444)
Observations	3,710	3,710
R-squared	0.346	0.378
Number of ccode	149	149
RMSE	0.663	0.663

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure xiv: Pooled Duration model with Fatalities

VARIABLES	(1) east asia	(2) europe	(3) FSU	(4) LA	(5) mid east	(6) south asia	(7) ss africa	(8) all
$onset_{t-1}$	0.711***	0.712***	0.714***	0.696***	0.715***	0.716***	0.679***	0.672***
	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.073)	(0.072)
APE_{t-1}	-0.825***	-0.734***	-0.690**	-0.775***	-0.865***	-0.763***	-0.567**	-0.750**
	(0.276)	(0.277)	(0.279)	(0.279)	(0.288)	(0.275)	(0.282)	(0.301)
$repression_{t-1}$	0.225***	0.238***	0.239***	0.246***	0.231***	0.235***	0.250***	0.249***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
$democ_{t-1}$	0.001	-0.001	0.001	0.014	0.010	0.006	0.007	0.015
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
$income\ equality_{t-1}$	-0.010	-0.016	-0.005	-0.021**	-0.007	-0.005	-0.000	-0.011
	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.012)
$gender\ equality_{t-1}$	-0.005***	-0.006***	-0.005***	-0.006***	-0.004**	-0.006***	-0.008***	-0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$adjacent\ conflict_{t-1}$	0.297***	0.349***	0.350***	0.334***	0.329***	0.348***	0.323***	0.312***
	(0.098)	(0.097)	(0.098)	(0.097)	(0.097)	(0.098)	(0.097)	(0.100)
$lnGDP\ pc_{t-1}$	-0.194***	-0.222***	-0.190***	-0.158***	-0.199***	-0.208***	-0.106**	-0.136**
	(0.047)	(0.049)	(0.047)	(0.047)	(0.047)	(0.049)	(0.049)	(0.053)
$lnGDP\ pc\ growth_{t-1}$	-0.030	-0.042	-0.038	-0.045	-0.040	-0.040	-0.017	-0.020
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)
$exports\ GDP_{t-1}$	0.001	0.000	-0.000	-0.002	-0.001	-0.001	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$internet_{t-1}$	0.003	0.003	0.003	0.002	0.002	0.003	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$lnpopulation_{t-1}$	0.192***	0.171***	0.164***	0.160***	0.172***	0.174***	0.188***	0.198***
	(0.028)	(0.026)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)	(0.029)
east asia	-0.262**							-0.021
	(0.125)							(0.187)
europe		0.254*						0.215
		(0.139)						(0.204)
former USSR			-0.161					0.099
			(0.134)					(0.206)
latin america				-0.337***				-0.066
				(0.099)				(0.177)
middle east					0.195			0.215
					(0.135)			(0.183)
south asia						-0.201		
						(0.150)		
sub-s africa							0.449***	0.427**
							(0.095)	(0.175)
Constant	-1.404***	-0.958*	-1.361***	-1.269***	-1.340***	-1.187**	-2.483***	-2.222***
	(0.480)	(0.498)	(0.491)	(0.466)	(0.480)	(0.475)	(0.539)	(0.590)
Observations	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710
AIC	2195	2197	2198	2189	2198	2198	2178	2182
Log Lik	-1083	-1084	-1085	-1080	-1085	-1085	-1075	-1072

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure xv: Onset Model with Regional Dummies

VARIABLES	(1) east asia	(2) europe	(3) FSU	(4) LA	(5) mid east	(6) south asia	(7) ss africa	(8) all
$\text{lnfatalities}_{t-1}$	0.756***	0.756***	0.756***	0.750***	0.755***	0.755***	0.754***	0.748***
	(0.0116)	(0.0116)	(0.0116)	(0.0118)	(0.0116)	(0.0116)	(0.0116)	(0.0118)
APE_{t-1}	-0.0286**	-0.0259**	-0.0260**	-0.0268**	-0.0296**	-0.0251**	-0.0218*	-0.0281**
	(0.0119)	(0.0118)	(0.0119)	(0.0118)	(0.0122)	(0.0118)	(0.0119)	(0.0125)
repression_{t-1}	0.0737***	0.0768***	0.0764***	0.0846***	0.0764***	0.0761***	0.0799***	0.0816***
	(0.0136)	(0.0135)	(0.0135)	(0.0137)	(0.0135)	(0.0135)	(0.0136)	(0.0139)
democ_{t-1}	0.00937	0.00934	0.0103	0.0219**	0.0163	0.00860	0.0128	0.0231**
	(0.00994)	(0.0101)	(0.0100)	(0.0106)	(0.0112)	(0.00998)	(0.00998)	(0.0117)
$\text{income equality}_{t-1}$	0.00703	0.00608	0.00876	-0.00243	0.0103	0.00603	0.0136	0.00212
	(0.00993)	(0.0115)	(0.0101)	(0.0105)	(0.00996)	(0.0100)	(0.0101)	(0.0130)
$\text{gender equality}_{t-1}$	-0.0308***	-0.0330***	-0.0324***	-0.0358***	-0.0260**	-0.0287***	-0.0389***	-0.0299**
	(0.00944)	(0.00948)	(0.00956)	(0.00944)	(0.0109)	(0.00966)	(0.00976)	(0.0119)
$\text{adjacent conflict}_{t-1}$	0.00990	0.0124	0.0119	0.0124	0.0111	0.0109	0.0131	0.00887
	(0.00890)	(0.00889)	(0.00899)	(0.00882)	(0.00885)	(0.00884)	(0.00883)	(0.00914)
lnGDP pc_{t-1}	-0.0317**	-0.0337**	-0.0319**	-0.0258*	-0.0345**	-0.0285**	-0.0190	-0.0151
	(0.0143)	(0.0148)	(0.0143)	(0.0144)	(0.0145)	(0.0145)	(0.0153)	(0.0162)
$\text{lnGDP pc growth}_{t-1}$	-0.00449	-0.00576	-0.00596	-0.00663	-0.00565	-0.00647	-0.00264	-0.00400
	(0.00831)	(0.00827)	(0.00838)	(0.00825)	(0.00826)	(0.00826)	(0.00837)	(0.00848)
exports GDP_{t-1}	0.0168	0.0132	0.0128	0.00986	0.0132	0.0127	0.0135	0.0143
	(0.0105)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0103)	(0.0106)
internet_{t-1}	0.00649	0.00674	0.00646	0.00448	0.00529	0.00595	0.00559	0.00298
	(0.0106)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0107)	(0.0106)	(0.0107)
$\text{lnpopulation}_{t-1}$	0.0781***	0.0715***	0.0714***	0.0702***	0.0728***	0.0700***	0.0754***	0.0784***
	(0.0113)	(0.0105)	(0.0106)	(0.0105)	(0.0106)	(0.0106)	(0.0106)	(0.0114)
east asia	-0.0474*							-0.112**
	(0.0287)							(0.0500)
europe		0.0139						-0.0845
		(0.0304)						(0.0521)
former USSR			-0.000152					-0.0624
			(0.0296)					(0.0511)
latin america				-0.0770***				-0.129***
				(0.0251)				(0.0473)
middle east					0.0441			-0.0449
					(0.0375)			(0.0532)
south asia						0.0691		
						(0.0424)		
sub-s africa							0.0612**	-0.0321
							(0.0253)	(0.0464)
Constant	-0.00855	-0.0156	-0.0127	-0.00100	-0.0183**	-0.0157*	-0.0305***	0.0551
	(0.00823)	(0.0100)	(0.00832)	(0.00871)	(0.00911)	(0.00803)	(0.0107)	(0.0414)
Observations	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710
R-squared	0.755	0.755	0.755	0.756	0.755	0.755	0.756	0.756
RMSE	0.472	0.472	0.472	0.471	0.472	0.472	0.471	0.471

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure xvi: Severity Model with Regional Dummies

VARIABLES	(1) east asia	(2) europe	(3) FSU	(4) LA	(5) mid east	(6) south asia	(7) ss africa	(8) all
lnduration_{t-1}	0.293***	0.295***	0.295***	0.294***	0.296***	0.296***	0.287***	0.286***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)	(0.0143)
APE_{t-1}	-0.134***	-0.124***	-0.120***	-0.124***	-0.127***	-0.125***	-0.108***	-0.119***
	(0.0188)	(0.0187)	(0.0189)	(0.0187)	(0.0193)	(0.0187)	(0.0188)	(0.0198)
repression_{t-1}	0.107***	0.117***	0.119***	0.122***	0.117***	0.117***	0.127***	0.119***
	(0.0188)	(0.0186)	(0.0187)	(0.0188)	(0.0186)	(0.0186)	(0.0186)	(0.0190)
democ_{t-1}	0.0189	0.0193	0.0195	0.0345**	0.0268	0.0231	0.0317**	0.0359*
	(0.0156)	(0.0160)	(0.0158)	(0.0166)	(0.0176)	(0.0157)	(0.0157)	(0.0184)
$\text{income equality}_{t-1}$	0.0148	0.0128	0.0250	0.00830	0.0223	0.0225	0.0398**	0.0388*
	(0.0156)	(0.0182)	(0.0159)	(0.0167)	(0.0157)	(0.0158)	(0.0158)	(0.0205)
$\text{gender equality}_{t-1}$	-0.0191	-0.0269*	-0.0215	-0.0283*	-0.0203	-0.0270*	-0.0500***	-0.0348*
	(0.0149)	(0.0149)	(0.0151)	(0.0149)	(0.0172)	(0.0153)	(0.0153)	(0.0188)
$\text{adjacent conflict}_{t-1}$	-0.0136	-0.00459	-0.00266	-0.00566	-0.00675	-0.00565	-0.00183	-0.00883
	(0.0141)	(0.0141)	(0.0143)	(0.0140)	(0.0140)	(0.0140)	(0.0139)	(0.0145)
lnGDP pc_{t-1}	-0.0387*	-0.0447*	-0.0399*	-0.0322	-0.0411*	-0.0409*	0.0111	0.00862
	(0.0226)	(0.0235)	(0.0227)	(0.0229)	(0.0229)	(0.0229)	(0.0241)	(0.0257)
$\text{lnGDP pc growth}_{t-1}$	-0.00485	-0.00957	-0.00742	-0.0108	-0.00998	-0.0100	0.00267	0.00462
	(0.0131)	(0.0131)	(0.0133)	(0.0131)	(0.0131)	(0.0131)	(0.0132)	(0.0134)
exports GDP_{t-1}	0.0288*	0.0152	0.0141	0.0105	0.0142	0.0140	0.0166	0.0251
	(0.0167)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0163)	(0.0162)	(0.0167)
internet_{t-1}	0.0286*	0.0292*	0.0282*	0.0261	0.0275	0.0287*	0.0251	0.0236
	(0.0169)	(0.0169)	(0.0169)	(0.0169)	(0.0170)	(0.0169)	(0.0168)	(0.0169)
$\text{lnpopulation}_{t-1}$	0.116***	0.0914***	0.0888***	0.0889***	0.0921***	0.0919***	0.106***	0.121***
	(0.0177)	(0.0165)	(0.0166)	(0.0165)	(0.0166)	(0.0166)	(0.0166)	(0.0179)
east asia	-0.177***							-0.137*
	(0.0454)							(0.0789)
europe		0.0429						-0.0507
		(0.0481)						(0.0823)
former USSR			-0.0602					-0.0286
			(0.0470)					(0.0807)
latin america				-0.0849**				-0.0292
				(0.0392)				(0.0741)
middle east					0.0333			0.0170
					(0.0594)			(0.0840)
south asia						-0.0334		
						(0.0671)		
sub-s africa							0.239***	0.189**
							(0.0401)	(0.0733)
Constant	-0.0413***	-0.0657***	-0.0512***	-0.0439***	-0.0611***	-0.0555***	-0.126***	-0.0842
	(0.0130)	(0.0159)	(0.0132)	(0.0138)	(0.0144)	(0.0127)	(0.0170)	(0.0654)
Observations	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710
R-squared	0.246	0.243	0.243	0.244	0.243	0.243	0.250	0.251
RMSE	0.747	0.748	0.748	0.748	0.748	0.748	0.744	0.744

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure xvii: Duration Model with Regional Dummies

VARIABLES	(1) east asia	(2) europe	(3) FSU	(4) LA	(5) mid east	(6) south asia	(7) ss africa	(8) all
lnprotest_{t-1}	0.536***	0.539***	0.535***	0.534***	0.530***	0.538***	0.537***	0.522***
	(0.0140)	(0.0139)	(0.0140)	(0.0140)	(0.0140)	(0.0139)	(0.0139)	(0.0141)
APE_{t-1}	-0.00474	0.00202	-0.00799	0.00186	0.0262	0.00329	-0.00455	0.00465
	(0.0199)	(0.0198)	(0.0200)	(0.0197)	(0.0204)	(0.0198)	(0.0200)	(0.0210)
repression_{t-1}	-0.0235	-0.0161	-0.0203	-0.0243	-0.0130	-0.0178	-0.0194	-0.0287
	(0.0197)	(0.0196)	(0.0196)	(0.0196)	(0.0195)	(0.0196)	(0.0196)	(0.0199)
democ_{t-1}	0.0822***	0.0816***	0.0914***	0.0642***	0.0446**	0.0816***	0.0811***	0.0365*
	(0.0169)	(0.0173)	(0.0171)	(0.0179)	(0.0188)	(0.0170)	(0.0170)	(0.0197)
income equality $_{t-1}$	-0.0370**	-0.0393**	-0.0418**	-0.0107	-0.0432**	-0.0366**	-0.0391**	-0.0655***
	(0.0168)	(0.0195)	(0.0170)	(0.0178)	(0.0168)	(0.0169)	(0.0170)	(0.0220)
$\text{gender equality}_{t-1}$	-0.00355	-0.00927	-0.0166	-0.00256	-0.0526***	-0.00220	0.00105	-0.0391*
	(0.0159)	(0.0159)	(0.0161)	(0.0158)	(0.0183)	(0.0163)	(0.0164)	(0.0200)
$\text{adjacent conflict}_{t-1}$	0.0269*	0.0331**	0.0236	0.0312**	0.0378**	0.0304**	0.0303**	0.0261*
	(0.0151)	(0.0151)	(0.0152)	(0.0149)	(0.0150)	(0.0150)	(0.0150)	(0.0154)
lnGDP pc_{t-1}	-0.0330	-0.0381	-0.0320	-0.0457*	-0.0161	-0.0285	-0.0520**	-0.0443
	(0.0242)	(0.0251)	(0.0242)	(0.0244)	(0.0244)	(0.0245)	(0.0259)	(0.0274)
$\text{lnGDP pc growth}_{t-1}$	0.00700	0.00377	-0.00366	0.00397	0.000859	0.00253	-0.00165	-0.00344
	(0.0140)	(0.0140)	(0.0142)	(0.0139)	(0.0139)	(0.0140)	(0.0142)	(0.0143)
exports GDP_{t-1}	0.0320*	0.0228	0.0214	0.0277	0.0195	0.0217	0.0209	0.0331*
	(0.0178)	(0.0174)	(0.0173)	(0.0174)	(0.0173)	(0.0174)	(0.0174)	(0.0178)
internet_{t-1}	-0.00110	-0.000429	-0.000669	0.00287	0.00693	-0.00192	0.000194	0.00996
	(0.0180)	(0.0181)	(0.0180)	(0.0180)	(0.0181)	(0.0180)	(0.0180)	(0.0181)
$\text{lnpopulation}_{t-1}$	0.199***	0.182***	0.189***	0.187***	0.176***	0.180***	0.177***	0.197***
	(0.0195)	(0.0182)	(0.0183)	(0.0182)	(0.0182)	(0.0182)	(0.0183)	(0.0197)
east asia	-0.120**							-0.168**
	(0.0486)							(0.0844)
europe		0.0354						0.0179
		(0.0514)						(0.0878)
former USSR			0.145***					0.0599
			(0.0504)					(0.0862)
latin america				0.145***				0.0121
				(0.0420)				(0.0791)
middle east					-0.304***			-0.314***
					(0.0638)			(0.0901)
south asia						0.101		
						(0.0717)		
sub-s africa							-0.0867**	-0.126
							(0.0429)	(0.0783)
Constant	0.0348**	0.0167	0.0104	0.00180	0.0621***	0.0197	0.0492***	0.104
	(0.0140)	(0.0170)	(0.0141)	(0.0147)	(0.0155)	(0.0136)	(0.0182)	(0.0699)
Observations	3,710	3,710	3,710	3,710	3,710	3,710	3,710	3,710
R-squared	0.392	0.391	0.393	0.393	0.395	0.392	0.392	0.398
RMSE	0.798	0.799	0.798	0.798	0.796	0.799	0.798	0.795

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure xviii: Protest Model with Regional Dummies