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DOCTORAL THESIS

The causes and consequences of violent conflict

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List of Abbreviations

CNA	Center for Naval Analyses
DDR	Disarment, Demobilization and Reintegration
DHS	Demographic and Health Survey
FARC	Revolutionary Armed Forces of Colombia
GADM	Global Administrative Area Database
GRACE	Gravity Recovery and Climate Experiment
IAT	Implicit Association Test
IDMC	Internal Displacement and Monitoring Center
IRA	Irish Republican Army
IS	Islamic State
ISIS	Islamic State of Iraq and the Levant
IV	Instrumental Variable
KDPI	Democratic Party of Iranian Kurdistan
NOAA	National Oceanic and Atmospheric Administration
OLS	Ordinary Least Squares
UCDP	Uppsala Conflict Data Program
UN	United Nations
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNICEF	United Nations International Children's Emergency Fund
UNRIC	United Nations Regional Information Center
SCAD	Social Conflict Analysis Database
SC-IAT	Single Category Implicit Association Test
SEDAC	Socioeconomic Data and Applications Center
SENA	National Training Service in Colombia
SPEI	Standardised Precipitation Evapotranspiration Index

Chapter 1

Introduction

1.1 Motivation

The social and economic burden of violent conflict for a society is substantial (Gates et al., 2012). First and foremost, millions of people have died in violent conflicts and even more persons have been injured (Spagat et al., 2009). Yet, apart from the battle-related deaths and injuries, the direct and short-term implications of violent conflict include physical destruction, economic recession, psychological distress, forced displacement, poverty and famine. But, they reach far beyond these short-term effects. Their legacy is long-lasting and complex.

After a rather peaceful period in the first decade of the 21^{st} century, the intensity of violent conflict in the world has risen again in the last 10 years[1] (Pettersson and Öberg, 2020). Major events that contributed to this rise are the Arab spring and the emergence of jihadist terrorist organizations, especially of ISIS. Currently, Syria, Libya and Yemen are experiencing devastating civil wars. Hence, violent conflict remains a challenge.

There are two striking patterns in violent conflict. First, they are regionally clustered. More specifically, they concentrate among developing countries, showing a clear correlation with economic wealth (Blattman and Miguel, 2010). Second, conflicts are persistent and recurring (Hegre et al., 2011). Collier et al. (2003) explains this path-dependent process of conflict with a conflict trap. He argues that the consequences of conflict increase the risk of another outbreak or ongoing violence, resulting in a vicious circle. Thus, in order to solve the challenge of violent conflict, this circle has to be broken.

International organizations and policymakers have faced the challenge with increasing peace-building initiatives, showing rather modest achievements. Promoting a new direction, the joint initiative by the United Nations (UN) and the World Bank 'Pathways to Peace' declares "a shift away from [only] managing and responding to crises [...] toward preventing conflict" (World Bank Group, 2018, p.iii). This highlights the two possible entry points how to address the vicious circle of conflict. On the one

[1]Chapter 2 provides a detailed overview of the recent trend in violent conflict.

hand, one can approach the structural factors causing conflict in order to prevent conflicts and on the other hand, one can focus on conflict resolution and peace-building. In both cases, a profound understanding of the causes and consequences of violent conflict is necessary to design effective protective actions and preventative policies.

Over the past decades, much work has investigated the causes and consequences of violent conflict.

The economic literature on the causes of conflict has identified several structural factors causing conflict, including poverty, rough terrain or the quality of institutions (Fearon and Laitin, 2003; Crost et al., 2016). Based on the greed and grievance theory (Collier and Hoeffler, 2004), the recent literature shows that easily extractable goods such as natural resources (Berman et al., 2017; Lei and Michaels, 2014; Dube and Vargas, 2013) but also foreign aid (Nunn and Qian, 2014; Crost et al., 2014) provide economic opportunities that motivate people to fight. At the same time, ideological reasons and grievance such as income inequality and ethnic or religious divisions (Esteban and Ray, 2011; Esteban et al., 2012; Arbatli et al., 2020; Basedau et al., 2016) determine the probability of conflict. Other theories explain the occurrence of conflict with the fighting of people over scarce, environmental resources (Homer-Dixon, 1994; Malthus, 1798). Following this argumentation, population growth (Brückner, 2010; Flückiger and Ludwig, 2018) and climatic shocks (Hsiang et al., 2013; Harari and Ferrara, 2018), which reduce agricultural output, contribute to a higher risk of conflict. Blattman and Miguel (2010) provide a detailed literature review.

Pioneers in the micro-economic literature on the consequences of violent conflict have analyzed the labor market effects of combat (Berger and Hirsch, 1983; Angrist, 1990; Angrist and Krueger, 1994). The recent literature focuses on the effects on non-combatants, especially on the identification of long-term effects and behavioral changes.

Motivated by early childhood development theories and the fetal origin hypothesis (Barker, 1995; Cunha and Heckman, 2007; Almond and Currie, 2011), numerous empirical papers have investigated the effects of conflict exposure during childhood. These studies show that persons exposed to conflict during childhood have lower mental and physical health statuses throughout their lives compared to conflict-unexposed persons (Minoiu and Shemyakina, 2012; Akresh et al., 2012; Valente, 2015; Kesternich et al., 2014; Singhal, 2019). They also suffer from worse labor market outcomes in adulthood (Kondylis, 2010; Annan, 2010). With respect to the human capital consequences, the findings of the studies are controversial. Some show substantial educational losses (León, 2012; Shemyakina, 2011; Akbulut-Yuksel, 2014; Bertoni et al., 2019; Di Maio and Nandi, 2013), whereas others find positive effects (Arcand and Wouabe, 2009; Valente, 2014).

The surge in behavioral economics has stimulated the analysis of conflict-induced behavioral changes. The empirical findings are still limited. Using experimental methods, Voors et al. (2012) find an increase in risk-loving behavior, whereas Callen et al. (2014) document more risk aversion with conflict experiences. Other behavioral changes include an increase in altruistic and violent behavior, more political participation, trust and cooperation (Bellows and Miguel, 2009; Gilligan et al., 2013; Bauer et al., 2017; Blattman, 2009; Jakiela and Ozier, 2019; Bauer et al., 2016; Couttenier et al., 2019; La Mattina, 2017).

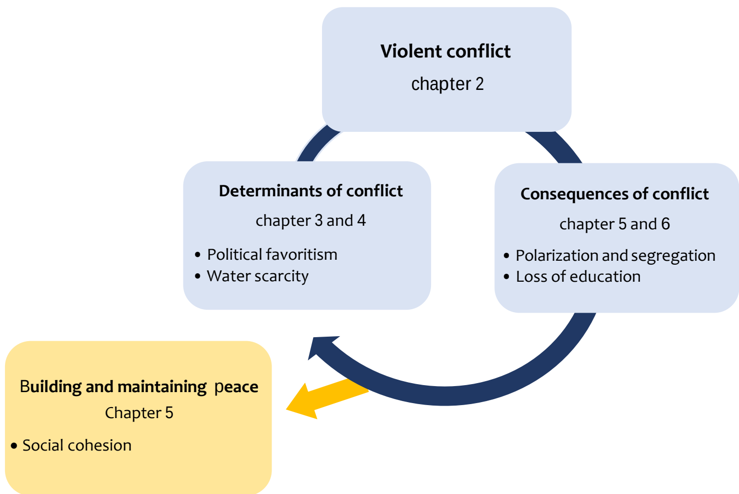
Taken together, the literature has identified numerous causes and consequences, contributing to the understanding of violent conflict. However, there are still open questions and considerable gaps. For instance, 'Why are the human capital consequences of conflict so diverse?' or 'How do climate-related shocks provoke fighting?'. Moreover, Blattman and Miguel (2010) highlight the gaps on the role of myopic and selfish leaders and identity in the conflict literature. In this dissertation, I make empirical contributions to close these gaps.

The aim of this dissertation is to help toward understanding violent conflict by investigating the complex relationships between conflict and multifaceted factors that maintain the vicious circle. The objective is twofold. First, to disentangle some of these interwoven relationships and identify chains of cause and effect. Second, to discuss the underlying mechanisms and incentives of actors with a focus on the role of policymakers.

In the research agenda, I present the concept of the thesis and how I approach the topic, whereas the thesis outline briefly summarizes the chapters.

1.2 Research agenda

FIGURE 1.1: Research agenda



For a full understanding, the thesis elaborates on various stages of the vicious circle and considers individual parts of it independently. Figure 1.1 presents the concept of the thesis. It illustrates how the chapters are related to each-other and to the conflict literature, using the framework of the conflict trap (Collier et al., 2003).

The thesis begins with the conceptualization of violent conflict in chapter 2.

The next two chapters serve to display the heterogeneity of causes of conflict by documenting the identification of two exemplified factors. In chapter 3, jointly with my co-author Andreas Kammerlander, I analyze the relationship between political favoritism and conflict. Chapter 4 links climate-related shocks to conflict. More precisely, it establishes a causal relationship between water scarcity and the likelihood of conflict.

An explanation of the recurrence of conflict is that the consequences of conflict provide breeding ground for another outbreak of violence. Therefore, chapter 5 and 6 identify two consequences of conflict. In chapter 5, together with my co-authors Marcela Ibañez Diaz and Lina Maria Restrepo Plaza, I address the segregation of populations caused by civil wars. We analyze discrimination and prejudice towards reintegrating ex-combatants in Colombia. Social exclusion and polarization cause grievance, motivating violence. The group of former fighters is especially pivotal as the opportunities and economic incentives to return to violence are often high. Chapter 6 deals with another potential factor that reinforces the feedback loop, namely the human capital consequences of conflict.

Peace-building and conflict preventive activities may rupture the vicious circle. Serving as an exemplar of such an intervention, we test one potential peace-building mechanism in chapter 5, targeting the conflict-induced segregation of populations.

On a methodological level, the studies use (quasi-)experimental methods to infer causality. This includes high dimensional fixed effects models, instrumental variable approaches and a lab-in-the-field experiment. In three of the four studies, I utilize novel, large-scale and spatial datasets, including satellite data on water mass movements, nighttime lights or irrigation, and newspaper collected information on geo-localized conflict events to investigate micro-economic questions at the macro level. Moreover, I combine multiple sets of geo-referenced survey data from the Demographic and Health Survey (DHS) or Afrobarometer to get precise information on individuals at a large scale. These new datasets allow me to establish a geographically precise link between conflict and other factors, improve the precision of the estimates and secure the external validity of the results. When necessary, I apply spatial econometric methods to address spatial dependence in the measurement. In chapter 5, I document a lab-in-the-field experiment, in which I collected my own data. The random assignment in the experiment assures a high internal validity. Additionally, micro-founded research complements the average effects found by cross-country studies with more context adjusted estimates, providing a more nuanced overall picture.

1.3 Thesis outline

The thesis begins in **chapter 2** with a brief description of the concept of violent conflict. It provides the reader with a definition of violent conflict and an overview of its recent prevalence around the globe. The main part of the thesis consists of four separate empirical studies, two of which deal with causes while the other two elaborate on the consequences of conflict. The studies are presented in a cause-effect order starting with the determinants and continuing with its consequences.

In **chapter 3**, jointly with my co-author Andreas Kammerlander, I analyze how political favoritism affects the likelihood and intensity of domestic conflict around the globe. The paper contributes to two strands of the literature. It has a close link to the literature on political favoritism (Hodler and Raschky, 2014b; De Luca et al., 2018a) and complements the literature on the causes of conflict. To our knowledge, this is the first study linking political favoritism to conflict. In the empirical analysis, we estimate the effect of political favoritism on conflict by comparing the leader's in-group's conflict exposure during the leader's time in office with other times. We also identify in which settings and through which mechanisms the effect occurs. The analysis combines self-gathered data on the birthplaces and the ethnic affiliation of national leaders[2] with geo-coded conflict events provided by Uppsala Conflict Data Program (UCDP). Our identification strategy is based on a high-dimensional fixed effects model with region and country-year fixed effects, and additional controls of regional, economic shocks. We find that the in-group of an autocratic leader is less exposed to violence during the leader's time in office as compared to other times. Our results indicate that the effect is driven by favoritism in the armed forces and other coup-proofing strategies.

Chapter 4 estimates the effect of an increase in water scarcity on conflict. It contributes to a growing literature on the effects of climate change on conflict (Hsiang et al., 2013; Harari and Ferrara, 2018). The novelty of the paper is that we (my co-authors Tilman Poser and Krisztina Kis-Katos, and I) can measure changes in water availability at the local level with the use of an innovative dataset. This allows us to establish a direct link between changes in available water mass and conflict. We use an instrumental variable approach for causal inference, instrumenting the shifts in water mass with the duration of local droughts. Using a grid cell-year panel of 68 countries in Africa, Latin America and the Caribbean over the years 2002 – 2017, the paper focuses on the differential effects by water supply and demand factors. The results indicate that water shortages, which are induced by climatic shocks, increase the risk of conflict. Access to groundwater dampens the susceptibility to climatic shocks, mitigating this effect. Water demand factors increase the risk of water scarcity, yet they show no differential effect on conflict.

[2]The data is publicly available on Harvard Dataverse; `https://doi.org/10.7910/DVN/YUS575doi:10.7910/DVN/YUS575`.

Chapter 5 focuses on the micro level, in particular on the civil war in Colombia. It also deviates methodologically from the other papers as it uses experimental methods for causal inference. In this chapter, Marcela Ibañez Diaz, Lina Maria Restrepo Plaza and I analyze community support for reintegration of ex-combatants in Colombia after the civil war. We contribute to the literature on peace building, specifically we provide empirical evidence on the perspective of the civil society towards reintegration of former fighters. In the experiment, we assess the extent of various kinds of discrimination and prejudice towards ex-combatants by university students. We also test whether mediated inter-group contact generates positive attitudes towards ex-combatants, sensitizing the society for the peace process. We exploit a natural setting in which trainees at a vocational school have developed business ideas and search for funding. Some of the trainees are former ex-fighters currently undergoing the governmental reintegration program. We run a crowd-funding campaign for them with over 1000 university students, in which we exogenously vary (1) the information that participants receive on who the beneficiaries are, (2) the information on the socio-economic characteristics and abilities of the beneficiaries and (3) the contact to a representative recipient. The 8 different treatments in the experiment, which uses a 2 x 2 x 2 between-subject design, allow us to measure discrimination towards former fighters and to evaluate the effectiveness of the inter-group contact. Our results show that non-discriminatory behavior coexists with discriminatory feelings of prejudice and fear. The mediated contact treatment increases positive attitudes towards reintegrating ex-combatants and financial support once crucial skills are highlighted.

In **chapter 6**, Krisztina Kis-Katos and I investigate the heterogeneous effects of conflict exposure during childhood on long-term consequences of human capital in Sub-Saharan Africa. We combine 66 rounds of DHS with geo-coded conflict events in 31 countries. Our diverse sample with multiple countries and conflict types allows us to contextualize the findings of previous country-specific case-studies (León, 2012; La Mattina, 2018; Shemyakina, 2011) and to elaborate on the role of mediators such as state capacity and conflict characteristics in the relation between conflict and education. Our main identification strategy compares educational losses of youth living within the same household, while controlling for local weather shocks and country-wide dynamics in education. We also apply an instrumental variable approach using the interaction of weather shocks and the distance to the next ethnic border as an instrumental variable for past local conflict exposure. We find substantial heterogeneity in the effect of conflict exposure during childhood on later life educational attainment. Education is on average unaffected by localized, low-intensity conflict. In contrast, high-intensity conflicts reduce educational attainment significantly. The human capital loss of conflict exposure is strongest in weak states and in non-state based conflicts.

Chapter 7 summarizes the main findings of the thesis and draws policy conclusions.

Chapter 2

Violent conflict

2.1 Definition

Violent conflicts are diverse in nature and have changed over time. Whereas armed conflicts between states have declined steadily in the last decades, internal conflicts have risen. Nowadays, they are the predominate type (Strand et al., 2019). Additionally, new forms of conflict have evolved such as terrorism and cyber wars. This diversity is also represented in the multiple definitions that exist of violent conflict. Its concept is controversial and discussed intensively in the literature especially by experts in international law (Paulus and Vashakmadze, 2009). The definitions have in common that two or more parties, mainly of organized character, with incompatible interests compete against each-other with the use of weapons. They deviate with respect to the requirements of battle-related deaths, the involvement of a governmental actor, the degree of organization of the actors or with respect to the inclusion of one-sided violence.

In this thesis, I follow the definitions of the conflict datasets used for the analysis. This is in chapter 3 and 6 the conceptualization of conflict by UCDP, and in chapter 4 by the Social Conflict Analysis Database (SCAD). Chapter 5 deals with the consequences of the internal conflict in Colombia, which complies with the UCDP definition. In both datasets, the unit of analysis and conceptualization is the conflict event. The UCDP defines a conflict event as

> "an incident where armed force was used by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date." (Sundberg and Melander, 2013, p.524)

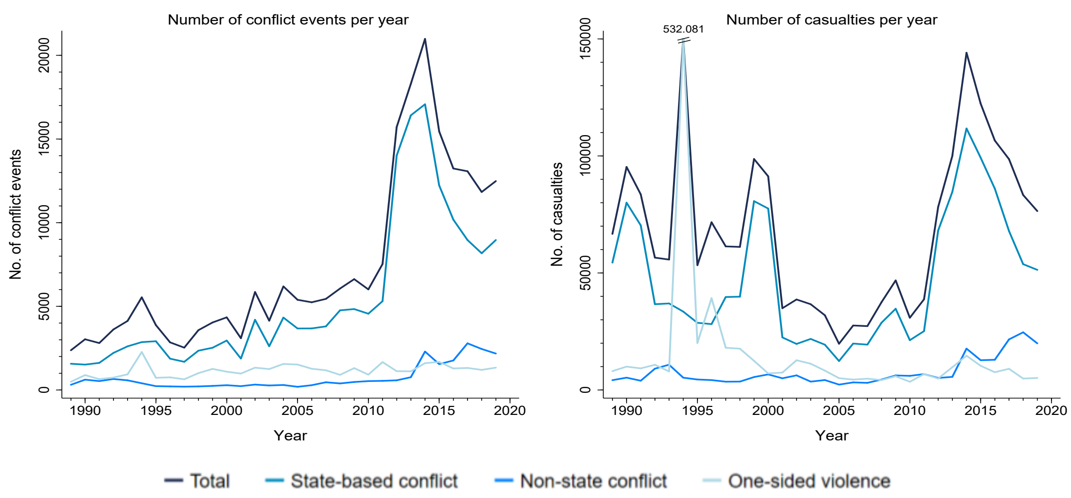
In contrast to the UCDP, SCAD collects information on social conflict. This includes mainly intrastate conflict events such as protests, riots, inter-communal violence, government violence against civilians, and excludes forms of armed conflict like organized rebellions, civil wars, and international war (Salehyan et al., 2012).

As both definitions still include a variety of conflict types, I further subdivide the events by its intensity and actors in the analysis. I follow the literature (e.g. León, 2012; Dube and Vargas, 2013; Do and Iyer, 2010) that commonly uses the number of fatalities or the duration of conflict as a measure of conflict intensity. Moreover, I classify conflicts into state and non-state based conflict depending on the involvement of governmental actors in the event.

2.2 Prevalence of violent conflict

In this section, I provide an overview of the temporal trends in violent conflict and its geographical distribution based on the UCDP data. Graph 2.1 depicts the temporal dynamic of the prevalence of violent conflicts in the world in the last three decades. The left graph shows the number of conflict events per year, whereas the right graph illustrates the dynamics in the intensity of violent conflicts, measured by the number of battle-related deaths. On top of the total numbers, I present the dynamic in individual conflict types. Conflict events are classified into three categories: (1) state-based conflict events including a governmental conflict actor, (2) non-state based conflict events and (3) violence against civilians.

FIGURE 2.1: The temporal dynamic of violent conflict



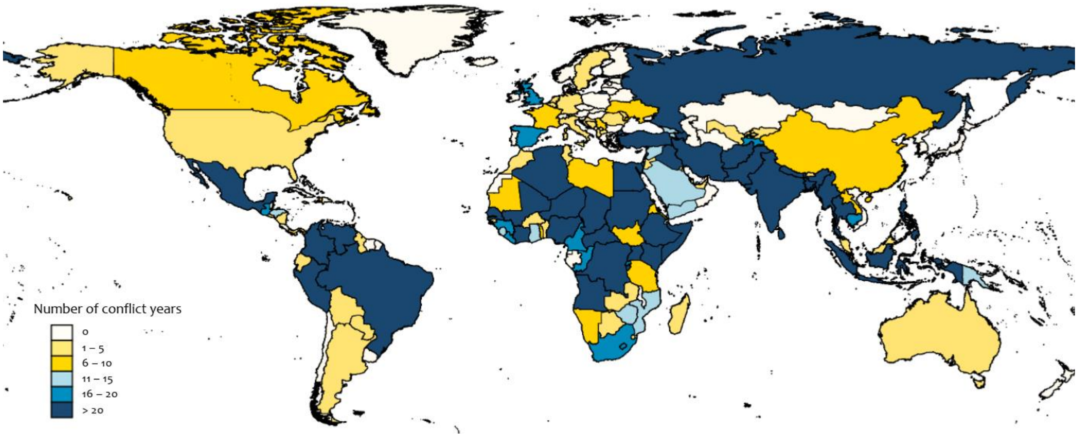
Source: UCDP.

Over the last three decades, the number of events has been on an upward trend. A sharp rise in the number of events occurred in 2011/12 with the outbreak of the Syrian civil war, the rise of IS and the Arabic spring. It peaks in 2014 reaching over 20.000 events. Though decreasing in the next years, it remains on a relatively high level. State-based conflicts are the most predominant type of conflict and are driving the increase.

The intensity of violent conflict follows a different trend. Conflict intensity decreased in 2000/01 to a long-term low in the first decade of the 21^{st} century but increased again in 2011. The graph presents two major peaks: one in 1994 and another one in 2014. With over 500.000 deaths, 1994 was the most violent year in the sample period. The major event that contributed to this high number is the genocide in Rwanda.

Fatalities sky-rocketed in 2014 with fighting of jihadist groups after the declaration of an Islamic caliphate by the IS (Pettersson and Öberg, 2020). The drop in casualties after 2014 is mainly driven by de-escalation of the wars in Syria and Iraq (Pettersson and Öberg, 2020). Taking both graphs together, one can see that there is a shift from high-intensity conflict events to low-intensity conflict events over time.

FIGURE 2.2: The geographical distribution of violent conflict



Source: UCDP.

Graph 2.2 presents the geographical distribution of violent conflict. It depicts the number of conflict years during 1989 – 2019 per country. The graph illustrates that many countries have experienced conflict events in the last decades, and that they are regionally clustered. Whereas Norway, Finland and Switzerland have been unaffected by conflicts, others experienced multiple conflict years. Germany experienced three of them.[1] Colombia was affected by conflict in all years except of 2016 and 2017. With respect to conflict intensity, the most affected countries are Rwanda, Syria and Afghanistan (Pettersson and Öberg, 2020).

The geographical distribution of violent conflict in combination with data availability determined the selection of the sample areas of the four studies. Chapter 3 is a global study taking into account that most countries have experienced at least one conflict event. The study in chapter 4 focuses on Africa and Central America, mainly driven by data availability on social conflict events. Chapter 5 deals with the internal conflict in Colombia, which is one of the longest active conflicts in recent history. Lasting over 50 years, the conflict officially ended with a peace treaty in 2016, enabling us to study discrimination in a post-conflict society. Yet after two peaceful years, violence associated with past conflict actors has increased again in 2018. Chapter 6 investigates the most conflict-affected continent, namely Africa.

[1] In 1990, British soldiers were killed by the IRA and in 1992 KDPI politicians by the Iranian government on German ground. In 2016, the IS terror attacks in Berlin occurred.

Chapter 3

Sending peace home?! The effects of political favoritism on conflict

Joint work with Andreas Kammerlander

3.1 Abstract

We investigate political favoritism in armed forces. More specifically, we estimate the effect of regional and ethnic favoritism on the likelihood and intensity of conflict and identify the channels of action. In a global sample, we combine geo-coded conflict data from the UCDP with self-gathered information on the birthplaces and ethnic affiliation of 836 political national leaders. Our identification strategy is based on a two-way fixed effects model with region and country-year fixed effects and additional controls of regional economic shocks.

The results show that regions in autocracies are less likely to experience moderate to high-intensity conflict years while they constitute the birth region of the national leader. In these regions, around 10% fewer casualties occur during that time. We also find evidence for ethnic favoritism. Our results indicate that favoritism in armed forces and other coup-proofing strategies reduce violence in the home region. Hence, we provide empirical evidence for an additional dimension of political favoritism.

3.2 Introduction

Mobutu Sese Seko, ex-president of Zaire, is an ideal example of a national leader engaging in political favoritism. During his time in office he embezzled more than US$ 5 billion (Guardian, 2004). A considerable amount of that money went directly to his hometown Glabolite that prospered extraordinarily during his time in office and eventually received the by-name "Versailles of the jungle" (Hodler and Raschky, 2014b). People from his ethnic tribe benefited by receiving powerful positions and public goods. Especially when granting higher positions in the armed forces, Mobutu relied on people from his home region Equateur and from his ethnic tribe, the Ngbandi, in order to secure loyalty (CIA, 2016). The newly created Special Presidential Division, for instance, consisted only of his own tribesmen and was led by his cousin (Wrong, 2000). To address internal threats, Mobutu centralized power and demonstrated the dependence of everyone on his favor by frequently reshuffling senior commanders and purging officers whom he regarded as politically unreliable (CIA, 2016; Acemoglu et al., 2004). "Personal loyalty to the president [was] the prime criterion for top military office" (Young and Turner, 1985, p. 274).

A similar story of political favoritism can be told about Saddam Hussein, the president of Iraq from 1979 to 2003. His hometown Tikrit became Iraq's city of palaces, where more than 60 palaces were built during his time in office (BBC, 2015). Under his rule, powerful positions were mainly given to members of his own Al-Bu-Nasir tribe and to people from the Tikrit area. More precisely, the residents of Saddam Hussein's birthplace, Al-Ujah (south of Tikrit), held power (BBC, 2015). His party banned tribal surnames possibly to conceal the major predominance of Saddam's tribe in government (New York Times, 2003). Moreover, he created the Special Republican Guard that consisted of members of his own tribe and family. It was installed in Bagdad and in Tikrit to ensure the protection of himself and his family and act against enemies of his regime (Malovany, 2017). Resources, such as funds but also skilled soldiers, were redirected from the regular armed forces to the Republican Guard (Powell, 2019). Promotions within the armed forces were largely based on favoritism rather than on competency or merit (Powell, 2019). "Corruption, favoritism, and nepotism were endemic" (Wright, 2008). These two examples of autocratic leaders engaging in political favoritism are no exceptions. Further anecdotal evidence is available about Bashar al-Assad, Muammar Gaddhafi, Eyadema Gnassingbe and others.

The anecdotal evidence has given rise to field of literature on political favoritism, highlighting that political leaders favor their in-group with respect to the allocation of public goods and transfers.[1] Hodler and Raschky (2014b) show that economic development in the home regions of political leaders increases disproportionally during their time in office. Dickens (2018) and De Luca et al. (2018b) find the same

[1]We refer to political favoritism as all kinds of actions by political leaders that favor their in-group, including rent-seeking activities, nepotism and corruption.

effect for the ethnic and co-ethnic homelands of the leaders. This increase likely stems from a privilege in the allocation of public transfers (Carozzi and Repetto, 2016), public goods like infrastructure (Do et al., 2017; Burgess et al., 2015), education and health care (Franck and Rainer, 2012; Kramon and Posner, 2016), or aid programs (Dreher et al., 2019). However, Kramon and Posner (2013) note that in-groups are favored with respect to certain goods, but not (or even disfavored) regarding other goods. This indicates substitution between goods that all contribute to economic and social well-being.

A dimension that has been disregarded by the literature is favoritism in armed forces and with respect to security precautions. Favoritism in armed forces is especially likely if political leaders fear a coup d'état. As the in-group is expected to be more loyal and well-disposed towards the leader, the recruitment process for crucial positions in the armed forces is potentially based on favoritism and personal connections rather than on merit. Whether these kinds of favoritism change the regional likelihood and intensity of conflict, and if so in which settings and through which mechanisms, are the research questions of this paper. More specifically, we identify the effect of political favoritism on conflict by comparing the leader's in-group's conflict exposure during the leader's time in office with other times. We differentiate between autocratic and non-autocratic regimes because autocrats face a greater threat of coup d'état compared to non-autocratic leaders (Thyne and Powell, 2016). Additionally, the characteristics of autocracies (elite-centered, fewer checks and balances and concentration of power) facilitate favoritism (e.g. Hodler and Raschky, 2014b; De Luca et al., 2018b).

Our analysis combines self-gathered data of the birthplaces and ethnic affiliations of 836 political leaders (Dreher et al., 2020) with geo-coded conflict data provided by the Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013; Stina, 2019) around the globe. We determine home regions on the second administrative level of a country based on the GADM database (GADM, 2019) and ethnic homelands based on the spatial settlement patterns of ethnicities from the GeoEPR2019 dataset (Vogt et al., 2015). We measure conflict both by the occurrence of at least one conflict event during a certain year in the respective region and by conflict intensity with the inverse hyperbolic sine of the number of battle-related deaths. Countries are classified into autocratic and non-autocratic regimes based on the World Bank Database of Political Institutions (Scartascini et al., 2018).

Using a region-year panel consisting of 44,025 regions and 27 years, our analysis controls for time-invariant regional effects and time-varying factors on the country level with two-way fixed effects. Region fixed effects absorb the geographic and socioeconomic variation in the average propensity to experience conflict and to become the birth region of the national leader, leader region,[2] in 44,025 regions across

[2]We will refer to the birth region of the national political leader as "leader region" for the duration of the leader's time in office.

the globe. We use country-specific time fixed effects (and provincial time trends) to capture yearly changes in the political and economic environment of the respective country (and to control for provincial changes in the economy and politics). Moreover, we account for time-variant regional factors like economic shocks and population growth by controlling for extreme weather events, natural-resource shocks and the logarithm of population density.

Our results show that regional favoritism reduces the intensity of conflict in the home regions of autocratic leaders. In autocracies, regions are 1.9 percentage points less likely to experience years with 25 and more conflict-related deaths while being the birth region of the current leader as compared to other times. Regions also experience on average around 10% fewer casualties during that time. The leader's ethnicity is less involved domestic conflicts during his/her time in office.

In the channel analysis, we consider three possibilities. First, concerning the *welfare channel*, we argue that the rise in economic development through political favoritism is likely to reduce the incentives to fight for citizens in the home region. We test this channel by conducting a mediator analysis using regional nighttime lights as a proxy for economic development. Second, in the *in-group favoritism channel*, we argue, based on the social identity theory (Tajfel and Turner, 1986), that leaders are more cooperative and benevolent towards their in-groups. Specifically, leaders may use less repression and state violence in their home regions and/or may increase security precautions in these regions. With the use of Afrobarometer data, we analyze whether more armed forces are installed in the home regions of the current leaders during their time in office. Moreover, we test whether leader regions experience fewer state violence against civilians. Third, the *coup-proofing channel* captures that leaders engage in coup-proofing strategies, such as the recruitment of senior officers from their in-groups and the purge of rivals to prevent internal threats. This results in a predominance of in-groups in the armed forces. Given the in-group bias, discriminatory behavior of the armed forces towards out-groups and vice versa are likely. Moreover, the dominance of the in-groups and the centralization of power encourage corruption especially in the home regions. We address this channel in two ways. First, using Afrobarometer data, we analyze whether the perception of public sector corruption of citizens differs when residing in the leader region as compared to other times. Second, we test if our baseline effect is more pronounced in countries with a higher probability of coups. Our channel analysis provides evidence for the 'in-group favoritism channel' and the 'coup-proofing channel'. The preferential treatment of in-groups in the recruitment and resource allocation within the military changes the intensity of conflict in autocratic leader regions. We find a stronger effect of political favoritism on conflict in countries that are more likely to engage in coup-proofing strategies.

We complement the political-favoritism literature by adding the dimension of conflict. Furthermore, we contribute to the literature on the determinants of conflict and the role of the state in conflicts. Do and Iyer (2010) show that more conflict-related deaths occur in poorer districts and in geographical locations that favor insurgents, such as mountains and forests. Additionally, the intensity of conflict has been linked to natural resources (Dube and Vargas, 2013; Berman et al., 2017), ethnic diversity (Esteban et al., 2012; Corvalan and Vargas, 2015), and income shocks (Harari and Ferrara, 2018; Hodler and Raschky, 2014a), among others. Since the feasibility hypothesis', state capacity has been argued to determine conflict (Fearon and Laitin, 2003; Collier et al., 2009). Hegre and Nygård (2015) point out that good governance can rupture the conflict trap, reducing the likelihood of conflict. On the local level, Wig and Tollefsen (2016) find that locations with better local institutions are less likely to experience conflict. They propose two channels. First, local institutional quality shapes the motivations of residents to engage in violence by affecting grievances. Second, governmental quality influences the cost of violence. If state presence in a locality is higher, insurgency is costlier.

The remainder of this paper is structured as follows. Section 2 offers a short literature review on the link between political favoritism and conflict, while section 3 describes the data and measurements used in the empirical analysis. Section 4 outlines the empirical strategy and discusses issues of identification. In section 5, the results are described, and further robustness checks are presented in section 6. Section 7 concludes.

3.3 Political favoritism and conflict

Political favoritism can affect the probability and intensity of conflict in a country through multiple channels. In the following, we highlight a multitude of possible pathways. Since these pathways are both positive and negative, the direction of the (net) effect is unclear ex-ante.

On the one hand, a leader region may face a higher likelihood of conflict as rebel groups are potentially keen to target the birth region when attacking the government due to its symbolic value. Furthermore, political favoritism raises inequality among regions (Hodler and Raschky, 2014b; Asher and Novosad, 2017), resulting in a higher risk of conflict along the regional borders due to relative deprivation. Especially if increases in inequality coincide with identity cleavages, they enhance group grievances and facilitate mobilization for conflict (Østby et al., 2009). Political favoritism can also have a conflict-increasing side effect. For instance, the beneficial treatment of the leader region in the distribution of foreign aid (Dreher et al., 2019) may incentivize rebel attacks stealing the aid (Nunn and Qian, 2014).

On the other hand, political favoritism can have a conflict-decreasing side effect. The gain in economic and social development through favoritism in the leader regions (Hodler and Raschky, 2014b; De Luca et al., 2018b; Kramon and Posner, 2016) raises the opportunity costs of fighting and alleviates grievances (Hodler and Raschky, 2014a; Miguel et al., 2004). Hence, the welfare gain in the home region reduces citizens' incentives to rebel. This is called the *'welfare channel'*.

Based on the social-identity theory, leaders may be more concerned about the well-being of members of their in-group compared to other citizens. This can result in a beneficial treatment of the in-groups with respect to safety precautions. For instance, leaders can mandate to install more security personnel in their home regions. The installment of armed forces is likely to deter attacks as it hinders insurgency (McDougall, 2009), although it can also shift fighting into the region. Additionally, leaders can command the armed forces to handle in-group members more softly, which would reduce the intensity of conflict in the home regions. We refer to this channel as the *'in-group favoritism channel'*.

Generally, autocratic leaders fear to be removed by coups. In order to protect themselves from internal threats, they engage in coup-proofing strategies (Quinlivan, 1999). Among these strategies are the recruitment of military officers from the in-groups (e.g. home region, family ties or ethnic affiliation) and the purge of rivals in order to secure loyal behavior of the armed forces (Quinlivan, 1999). This results in a predominance of the in-groups in the armed forces. Following the parochial-altruism theory (Choi and Bowles, 2007), armed forces are then positively biased towards the home regions (in-group) and have a tense relationship with other regions (out-group). Similarly, regions which see themselves excluded from power may perceive the armed forces with animosity, whereas citizens of the home regions may be sympathetic towards them, increasing the likelihood of conflicts in non-leader regions and reducing the likelihood in home regions.

A second coup-proofing strategy is to reduce the power of the military by reshuffling and rotating officer positions, diminishing the capabilities of the military with the division of the army into multiple forces or the establishment of a paramilitary group that controls the regular army (Sudduth, 2017). These methods reduce the effectiveness of the military in general, and increase the difficulty to unite all military forces. They also lead to a shift in resources and skills away from the military and possibly towards a paramilitary group consisting of loyal in-group members (Pilster and Böhmelt, 2011).

Other coup-proofing strategies aim to reduce the willingness of the armed forces to start a coup by providing personal interests and incentives of officers and aligning them with those of the leader (Sudduth, 2017). One tool to secure loyalty and minimize defection is corruption (Harm and Charap, 1999). Pivotal groups, such as senior officers, may be bribed by the leader to maintain power (Acemoglu et al., 2004). The offering of private privilege in exchange for political loyalty can reduce the likelihood of revolts and thus conflict (Fjelde, 2009). We refer to these mechanisms as the *'coup-proofing channel'*.

The extent of political favoritism and its effect on conflict depend on the form of government. Whereas in democracies, the national leader is elected or appointed by a parliament, in other systems, the leader inherits the office or takes over via coup. The distinct forms certainly provide different incentives (how) to run for office and affect the motivation to engage in political violence. Additionally, the form of government determines the extent to which political favoritism is possible. Based on the findings of previous literature (Hodler and Raschky, 2014b; De Luca et al., 2018b), we hypothesise that political favoritism is more likely in autocratic than in other regimes. Autocratic leaders concentrate more power and face fewer checks and balances compared to non-autocratic leaders, which facilitates political favoritism. Hence, we differentiate between autocratic and non-autocratic systems.

3.4 Data and measurement

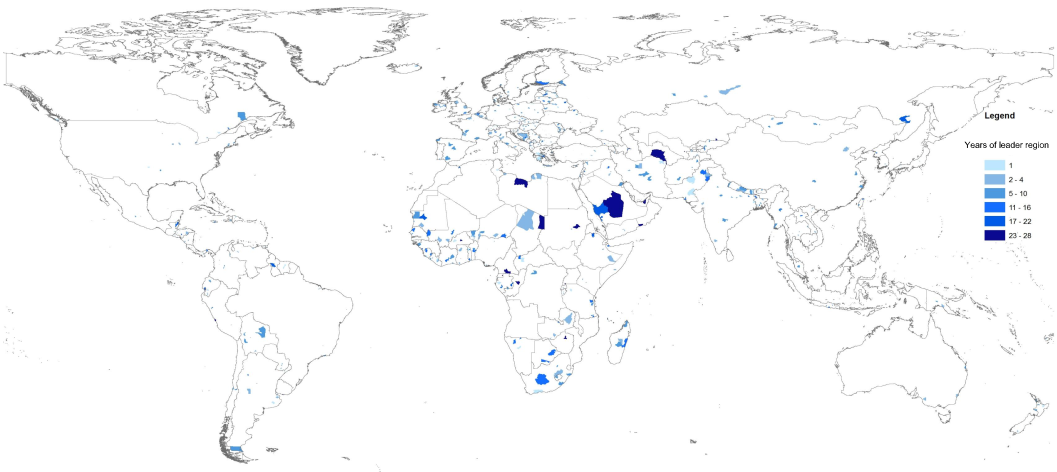
In the empirical analysis, we combine geo-coded conflict-event data from the UCDP Georeferenced Event Dataset (GED) global version 19.1 (Sundberg and Melander, 2013) with information on the birth places of political leaders from the Political Leaders' Affiliation Database (PLAD) (Dreher et al., 2020). Our dataset is based on several further sources that, together with detailed variable definitions and measurements, are listed in the Data appendix. The unit of observation is region-year, whereby 'region' refers to the second administrative level of a country provided by the GADM dataset v3.6 (GADM, 2019). Our final sample consists of a panel dataset with 44,025 regions in 2,963 provinces and 172 countries over the years 1989 – 2015 resulting in a total of 1,177,805 observations.

The main explanatory variables are *Leader autoc* and *Leader non-autoc*, which are defined as dummy variables that take the value of 1 if a region is the birth region of the current national leader in an autocratic and non-autocratic political regime. In years with a change in office, two regions can be defined as the leader region. We identify the birth regions of national leaders with the PLAD database. Figure 3.1 depicts the leader regions.

Our dependent variables are three different indicators of conflict. Conflict is measured a) as a dummy variable, indicating if there is any conflict event in a given region and year, b) as a dummy variable for conflict events resulting in at least 25 battle-related deaths in a given region and year or c) by the inverse hyperbolic sine function of the number of casualties. The variables are based on the UCDP GED dataset, which offers information on the exact geographical location of conflict events, the involved actors and the corresponding reported number of casualties from 1989 until 2015. In the channel analysis, we subdivide the conflict events based on the UCDP definition into state-based and non-state-based conflicts as well as one-sided violence.

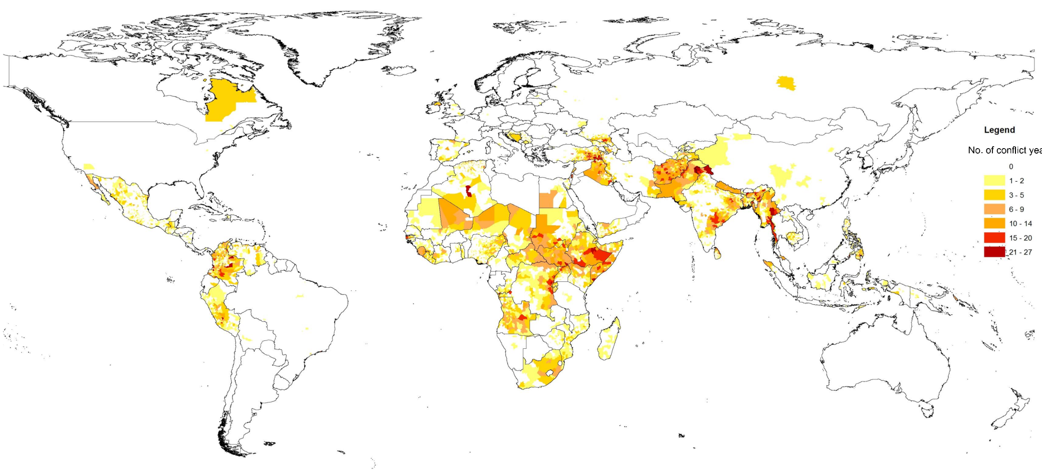
The frequency of conflict, measured by the number of years in which at least one conflict event occurred, is shown in figure 3.2. Conflict events are regionally clustered,

FIGURE 3.1: Spatial distribution of leader regions



Note: The figure reports the number of years of being the leader region for each second administrative region over the time period of 1989 – 2015. A leader region is the birth region of the effective leader during the time in office. Sources: Archigos, own data collection.

FIGURE 3.2: Spatial distribution of conflict years



Note: The figure reports the number of conflict years for each second administrative region during the sample period 1989 – 2015. A conflict year is a year in which at least one conflict event occurred in the region. Source: UCDP.

with a higher frequency of conflict events in Africa, the Middle East and parts of Asia. Most regions experienced 0 years of conflict, others were exposed to conflict during the entire sample period. The average probability of a region to experience a conflict event in any given year is 2.2% in our sample. On average, 1.45 conflict-related casualties per region and year occur. The average probability of conflict rises to 3.5% (6.37 casualties) for regions in autocracies and drops to 1.9% (0.6 casualties) in non-autocratic countries. In general, leader regions have a higher likelihood to experience conflict (6.24% with an average of 16.06 casualties per year). Similarly, the probability (8.03% vs 5.79%) and intensity (58.02 vs 2.83 casualties) of conflict is higher in autocracies. This unconditional comparison shows a) that autocracies are more prone to conflict than non-autocracies and b) that leader regions on average experience more conflicts than non-leader regions.

Political favoritism is not only targeted towards the birth regions of national leaders but also towards their ethnic in-groups (De Luca et al., 2018b). We use the information on the ethnic affiliation of national leaders provided by the PLAD dataset in order to link the leaders' ethnicity to conflict in two different ways. First, we stick to the regional approach and observe the conflict exposure of ethnic homelands based on the GeoEPR2019 dataset (Vogt et al., 2015). Second, we link ethnicity to conflict via (ethnic non-governmental) conflict actors provided by the Geographical Research On War Unified Platform (Growup) database (Girardin et al., 2015). This allows us to observe whether ethnic groups of national leaders are less involved in conflict events while the leaders are in office. To do so, we create dummy variables that indicate the ethnic homelands of the current political leader and identify the conflict actors belonging to the same ethnicity as the current leader. Analogous to the birth regions, we separate by political regime type.

In order to investigate the channels of action, we use geo-localized data from the Afrobarometer rounds 1 to 6. We aggregate the individual survey data at the second administrative level. This provides us with regional measures for the presence of state forces (military or police), trust and evaluated performance of the national leaders, and measurements of corruption. Since the Afrobarometer data is only available for 35 countries and at most 6 years, the sample is reduced to around 7000 observations.

A detailed description of all variables used can be found in the data appendix, and table 3.1 provides the descriptive statistics of the main variables.

TABLE 3.1: Summary statistics

Variable	Obs (1)	Mean (2)	SD (3)	Min (4)	Max (5)
Regional favoritism					
Conflict	1,177,805	0.02	0.15	0	1
Number of casualties	1,177,805	1.47	311.39	0	321,999
Leader region	1,177,805	0.00	0.06	0	1
Autocratic regime	1,177,805	0.13	0.34	0	1
Flood (sum of months)	1,177,805	2.26	2.14	0	12
Drought (sum of months)	1,177,805	2.00	2.03	0	12
Ln(population)	1,177,805	11.83	1.70	0.99	16.76
Oil x ln(price)	1,177,805	0.70	1.45	0	4.65
Gas x ln(price)	1,177,805	0.80	1.67	0	5.19
Ethnic favoritism					
Ethnic leader homeland region	14,954	0.16	0.36	0	1
Any conflict per ethnic homeland	14,954	0.26	0.44	0	1
Number of casualties per ethnic homeland	14,954	189.03	6182.72	0	524,477
Ethnicity leader region	15,094	0.16	0.36	0	1
Any conflict per ethnicity	15,094	0.05	0.22	0	1
Number of casualties per ethnicity	15,094	39.16	493.23	0	30,628
Channel analysis					
Number of state casualties	1,177,805	0.52	32.53	0	16,060
Number of non-state casualties	1,177,805	0.08	5.77	0	2,494
Number of civilian casualties by gov	1,177,805	0.24	66.14	0	44,310
Polity 2 score	1,157,668	5.52	5.37	-10	10
Nighttime lights	957,939	6.75	12.04	0	63
Army	7,757	0.10	0.26	0	1
Police	7,763	0.32	0.36	0	1
State force	7,763	0.25	0.28	0	1
Trust leader	8,131	1.82	0.67	0	3
Performance leader	8,137	2.82	0.61	1	4
Activism	8,236	0.98	0.59	0	5
Corruption index	8,336	2.42	0.43	1	4
Political corruption	8,190	2.21	0.49	1	4
Police corruption	7,791	2.63	0.47	1	4
Coup	1,177,805	0.14	0.35	0	1
Resource	1,177,805	0.13	0.33	0	1
Ethnic	1,177,805	0.51	0.50	0	1

3.5 Econometric model and issues of identification

To infer the effect of political favoritism on conflict, we exploit the spatial and temporal variation of leader regions in 172 countries over the years 1989 – 2015. We run the following regression:

$$\begin{aligned} Conflict_{rct} = \ & \beta_1 Leader\ autoc_{rct-1} + \beta_2 Leader\ non\text{-}autoc_{rct-1} \\ & + \mathbf{X}'_{rct-1}\theta + \alpha_r + \mu_{ct} + \epsilon_{rct}, \end{aligned} \tag{3.1}$$

where $Conflict_{rct}$ represents one of our three conflict outcomes of region r located in country c in year t. The main explanatory variables are $\textit{Leader autoc}_{rct-1}$ and $\textit{Leader non-autoc}_{rct-1}$. These are two indicator variables identifying the region r that is, in year t, the birth region of the current leader of country c in either an autocratic or non-autocratic regime. We use the lagged form of the main explanatory variables for two reasons. First, the leader region is determined on a yearly basis. Thus, measurement error occurs due to the fact that leaders may take office at the middle or end of a year. Second, it is likely that the allocation of public goods and transfers takes some time to be carried out in a bureaucratic system (Hodler and Raschky, 2014b). In all regression models, β_1 and β_2 are the coefficients of interest that capture the average effect of political favoritism on conflict in autocratic and non-autocratic countries. $\mathbf{X}_{rct-1}$ is a vector of control variables including weather and natural-resource price shocks as well as population growth. All control variables enter the regression in a lagged form. α_r and μ_{ct} describe region and country-year fixed effects, whereas ϵ is the error term. We cluster the standard errors at the country level.

The determination of a political leader is not random but follows political, social and economic causes. Dal Bó et al. (2017) show that politicians are well educated and often stem from richer households. Hence, regions that are better developed and have a higher human capital share are more likely to be the birth region of the national leader. Yet, these regions are less likely to be exposed to conflict due to higher opportunity costs of fighting (Do and Iyer, 2010; Østby and Urdal, 2011). To account for the heterogeneous initial conditions of regions that determine the likelihood of the national leader to originate from this region and experience conflict, our regression model includes region fixed effects (α_r) absorbing all kinds of time-invariant factors influencing the likelihood to be the birth region of a national leader and to experience conflict. Country-year fixed effects μ_{ct} of 172 countries and 27 years absorb nationwide shocks in a flexible manner. They account for changes in the political system such as election reforms, global economic crises or changes in the relevance of political topics.

Region fixed effects deal with time-invariant differences of regions. Yet, time-varying factors, such as regional economic development, can still confound the estimates, as recent regional economic conditions determine political preferences and behavior (Bagues and Esteve-Volart, 2016; Brunner et al., 2011; Chen et al., 2005) and at the same time affect the likelihood of conflict (Miguel et al., 2004; Hodler and Raschky, 2014a). Additionally, political trends such as provincial independence efforts can influence election outcomes and result in political violence. We address these potential endogeneity issues in two ways:

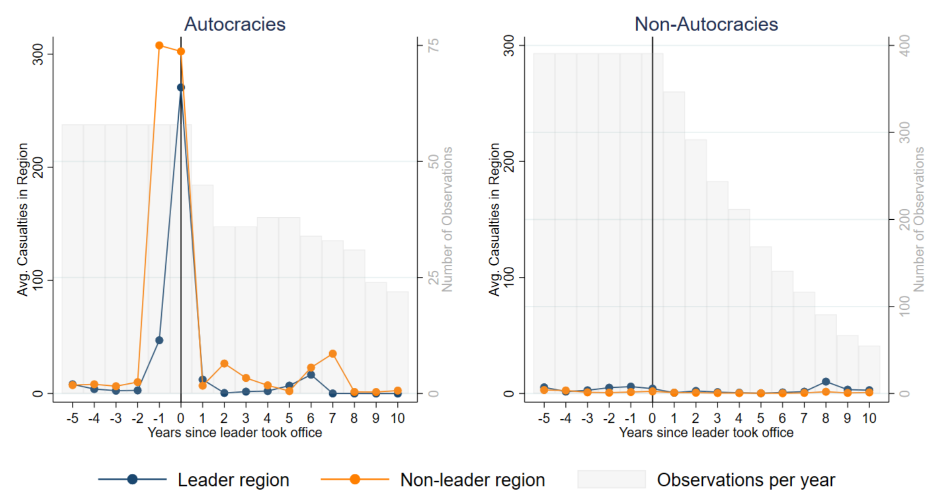
First, our regressions control for two major regional economic shocks with the inclusion of weather and natural-resource price shocks. Extreme weather events have a crucial impact on the local economy. Periods of drought or abundant rain not only influence the agricultural productivity and that of downstream industries, but also limit the transportation of goods and persons. In the long run, they also affect consumer prices (Ding et al., 2011). Natural resources are another important economic factor on the local level. We interact the world-market price of oil and gas with indicator variables that determine whether oil or gas deposits are present in a region and include them as controls. As a robustness check, we add price shocks of 10 further major minerals into the regression model in the same way. On top of that, we control for population growth. Population growth means a higher number of potential voters and a bigger pool of potential candidates to run for office. Thus, the likelihood that a leader originates from a certain region raises with the increase of its population. Following the logic of the Malthusian theory, population growth increases the likelihood of conflict as there is a stronger competition over scarce resources (Brückner, 2010).

Second, we provide further robustness checks that address potential omitted variable biases. We run an additional regression that includes provincial time trends, accounting for the average political, social and economic development in 2,963 provinces. Moreover, we control for past conflict experiences in the country and investigate pre-trends. The robustness checks validate our main results.

3.6 Results

3.6.1 Descriptive results

FIGURE 3.3: Evolution of conflicts before and after leader took office



Note: The figure reports the average number of casualties in leader regions and non-leader regions before and after a leader took office. 'Autocracies' and 'Non-Autocracies' refer to 'stable' regimes, where a political regime has already existed for at least 5 years. Countries that recently switched from a non-autocracy to an autocracy are dropped from the sample in this figure.

Figure 3.3 presents the unconditional descriptive evidence. It shows the average number of casualties per region before and after the assumption of office by the new national leader. In the left graph, we report the conflict trend for autocracies and in the right for non-autocratic regimes. To avoid large changes in the sample composition, we omit countries that have recently switched political regimes in the observed time period.[3] To identify any possible political favoritism, we distinguish between the home regions of national leaders and other regions.

The higher conflict intensity in autocracies, as described in the data section, is striking. The intensity (and probability) of conflict is higher in autocracies than in non-autocracies at any time. Especially in t=-1 and 0, the difference in the number of casualties between the political regimes is large. While the average number of casualties augments to close to 300 in autocracies, no increase can be found in non-autocracies. This strong rise in casualties before and as a leader comes into power implies the prevalence of coups or election violence in autocracies. We therefore specifically test if our findings are driven by coup d'états and the way in which power was seized.

Referring to the difference between leader and non-leader regions, the increase in violence in t=-1 and t=0 in autocracies can be observed in both. Nevertheless, the increase is stronger in non-leader regions. In the years before the immediate takeover period ($t < -1$), the difference between the (soon-to-be) leader regions and other regions is very small. After taking office, the conflict intensity of leader regions is lower or equal to non-leader regions. The right graph documents only small disparities between leader and non-leader regions in non-autocratic regimes throughout the sample period.

Overall, we observe more fatalities in autocracies than in non-autocracies, especially before a leader takes office. Leader regions have a lower number of casualties compared to non-leader regions in autocracies but not in other political regimes. While the aforementioned correlations are informative, we cannot interpret them in a causal way, since 3.3 only shows unconditional relations over time. In the following section, we thus proceed with a more thorough and robust regression analysis.

3.6.2 Regional favoritism and conflict

To establish a baseline result, we regress our conflict outcomes on the autocratic and non-autocratic leader-region indicators. The results are presented in table 3.2. In column 1, we use our broad conflict measure, whereas column 2 focuses on conflict years with moderate to high intensity. In this specification, a conflict year refers to a year with at least 25 battle-related deaths. Column 3 reports the results on the outcome variable of the inverse hyperbolic sine of the number of casualties. All regressions include region and country-year fixed effects as well as standard controls.

As shown in column 1 of table 3.2, there is no significant difference in the likelihood of conflict in leaders' birth regions during their time in office compared with other times. The estimates in column 2 show a statistically significant and negative coefficient

[3]We omit countries that have switched from an autocratic to a non-autocratic regime in the last 5 years or vice versa.

of the autocratic leader region dummy on medium to high intensity conflict years. More specifically, a region is 1.9 percentage points less likely to experience a conflict year with at least 25 casualties while being the leader region as compared to other times. Relative to the average likelihood of such a conflict year in autocratic leader regions (3%), the magnitude of the effect is huge. We find no significant difference in the likelihood of conflict among regions in non-autocratic regimes.

TABLE 3.2: Regional favoritism, autocracy and conflict

	Any conflict (1)	**Conflict (death $\geq$ 25)** (2)	**IHS(casualties)** (3)
Leader autoc$_{t-1}$	-0.004	-0.019**	-0.099**
	(0.009)	(0.008)	(0.043)
Leader non-autoc$_{t-1}$	-0.002	0.004	-0.004
	(0.005)	(0.004)	(0.019)
Observations	1,177,805	1,177,805	1,177,805
R-squared	0.364	0.264	0.387

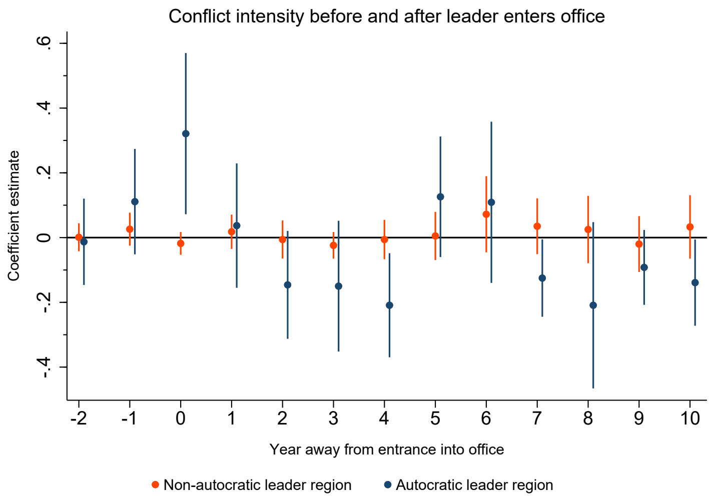
Note: The table reports OLS regression estimates of regressing our conflict outcomes on the lagged leader region dummies. Unit of observation is the yearly second administrative level. All regressions include region and country-year fixed effects as well as controls for weather and natural-resource shocks and population growth. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

However, the threshold of 25 battle-related deaths is arbitrary. A more flexible way to account for conflict intensity is by recording the number of casualties directly. The estimates in column 3 show that autocratic regions on average experience around 10% fewer casualties per year while being the birth region of the current leader than at other times. Again, we find no indication of political favoritism with respect to conflict in non-autocratic systems. Given that over 80% of our country-year observations are non-autocratic, we also find no significant coefficient on a joint indicator of being the leader region. The results are shown in table A.1 in the appendix.

3.6.3 Time dynamics

In the baseline analysis, we lagged the explanatory variables by one year as we assume that, for instance, the allocation of public goods and transfers may not be effective at once. Yet, it is possible that the effect arises immediately or that leaders need a longer time in office until they can engage in favoritism. Figure 3.4 shows how the conflict intensity in leader regions evolves over time conditional on country-year and region fixed effects as well as our standard controls. Whereas in non-autocratic leader regions, there is no change of conflict intensity over time, it varies visibly for autocracies. The graph depicts on average more battle-related deaths in the year of taking office in autocratic leader regions, hinting election violence. Afterwards, the intensity of conflict gradually decreases. It reaches a statistically significant, negative difference four years after the entrance into office. The estimation coefficients remain negative in the following years except for the years 5 and 6. A potential explanation for this rise is that office terms end and the re-elections of leaders are accompanied by violence. We find no statistical significant difference in conflict intensity in years prior to taking office, reassuring us that our results are not driven by pre-trends. Hence, we conclude that political favoritism affects the intensity of conflict after the autocratic leader has held office for a few years.

FIGURE 3.4: Time dynamics



Note: The figure reports the development of conflict intensity in the leader regions over time.

3.6.4 Ethnic favoritism and conflict

The anecdotal evidence and the previous literature on ethnic favoritism (De Luca et al., 2018b; Franck and Rainer, 2012; Dickens, 2018) suggest that political leaders may not only change the allocation of public goods and transfers to the benefit of the leaders' birth regions but also to the benefit of the leaders' ethnic tribes. To check whether members of the leaders' ethnicity are affected differently by conflict, we conduct two further pieces of analysis. First of all, we follow the approach of De Luca et al. (2018b) and test whether ethnic homelands of political leaders are less affected by conflict during their time in office. The results are reported in column 1 and 2 of table 3.3. The coefficients on *Ethnic leader autoc*$_{t-1}$ and *Ethnic leader non-autoc*$_{t-1}$ are statistically insignificant in both model specifications. Hence, we find no indication of a change in the risk and intensity of conflict in ethnic homelands with the leader's ethnic affiliation.

Given that in some countries, there is no geographical segregation of ethnic groups and people move substantially within countries, maps of ethnic homelands are prone to measurement errors. Moreover, whereas certain public goods and transfers have a geographical dimension, for instance the construction of roads, the distribution of others is targeted individually. Therefore, as a second approach, we depart from the regional strategy and analyze whether persons belonging to the leader's ethnicity engage less in conflict during the leader's time in office. This changes our unit of

TABLE 3.3: Ethnic favoritism, autocracy and conflict

	Any conflict	**IHS(casualties)**	**Any conflict**	**IHS(casualties)**
	(1)	(2)	(3)	(4)
Unit of observation	Ethnic homeland		Ethnicity	
Ethnic leader autoc$_{t-1}$	-0.011	0.035	-0.114**	-0.845***
	(0.028)	(0.163)	(0.051)	(0.315)
Ethnic leader non-autoc$_{t-1}$	-0.008	-0.068	-0.012	-0.096
	(0.020)	(0.124)	(0.018)	(0.118)
Observations	14,954	14,954	15,094	15,094
R-squared	0.757	0.821	0.657	0.706

Note: The table reports OLS regression estimates of regressing (1-2) any conflict or the number of casualties in the ethnic homelands and (3-4) any conflict or the number of casualties per ethnicity (of non-state-based conflicts) on the indicator variables of ethnic leader affiliation. All regressions include country-year, standard controls and (1) ethnic home region fixed effect or (2) ethnicity fixed effects. Standard errors are clustered at the country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

observation to an ethnicity-year panel. Based on the ACD2EPR dataset provided by the Growup data project, we identify the ethnic affiliation of non-governmental conflict actors and count the number of battle-related casualties per ethnicity in a country. A non-governmental conflict actor is defined as belonging to an ethnicity if the group recruits from the respective ethnic group and has announced that it is operating on behalf of this group (Wucherpfennig et al., 2012). The results are presented in column 3 and 4 of table 3.3. The estimates in column 3 show that an ethnicity is less likely to be involved in any conflict event in the country while one of its members is the national leader as compared to other times. The ethnicity also experiences fewer battle-related deaths during that time (column 4). Thus, we conclude that organized ethnic groups belonging to the same ethnicity as the current leader are less likely to be involved in conflict during the leader's time in office.

3.6.5 Channels

Political leaders may shape the intensity of conflict within a country in various ways. We consider three of these channels: the *welfare channel*, the *in-group favoritism channel* and the *coup-proofing channel*.

The welfare channel
We investigate the welfare channel in two ways. First, we follow Hodler and Raschky (2014a), showing that leaders' birth regions have a faster economic growth during their time in office, and Hodler and Raschky (2014b), linking economic development to conflict. Table 3.4 presents the results. Column 1 shows that in our sample and with the classification of countries into autocratic and non-autocratic the economies of autocratic leaders' birth regions do not grow faster (measured by nighttime light intensity) during the leaders' time in office than at other times. However, we find a significant negative correlation between economic development measured by night-time lights and the number of battle-related deaths, as shown in column2. Given that

we find no welfare effect of regional favoritism in autocratic countries, it appears less likely that a part of the reduction in conflict intensity in home regions of autocratic leaders results of the gain in economic development caused by regional favoritism.

TABLE 3.4: Welfare channel

	Ln(nightlight)		IHS(casualties)	
	(1)	(2)	(3)	(4)
Leader autoc$_{t-1}$	0.013		-0.09969**	-0.09978**
	(0.041)		(0.04587)	(0.04586)
Leader other$_{t-1}$	0.038*		0.00998	0.00973
	(0.019)		(0.01808)	(0.01804)
Ln(nightlight)		-0.007**	-0.00666**	
		(0.003)	(0.00305)	
Observations	957,939	957,939	957,939	957,939
R-squared	0.950	0.412	0.412	0.412

Note: The table reports OLS regression estimates of regressing the inverse hyperbolic sine function of the number of casualties on the lagged indicators of (non-)autocratic leader regions and the logarithm of nighttime light. Column 1 regresses lagged leader region indicators on the logarithm of nighttime light. Regression models as specified in table 4.2. *** p<0.01, ** p<0.05, * p<0.1.

Another way to test and measure the welfare channel is by comparing the effects of being the leader region on the intensity of conflict with and without controlling for economic development. If the reduction in conflict intensity is caused by an increase in welfare in the home region, the effect should be absorbed by inclusion of nighttime light into the regression equation. The results are shown in column 3 and 4. A comparison of the magnitudes of the estimates of autocratic leader regions reveal a marginal smaller coefficient in the model controlling for nightlight. Hence, we conclude that nighttime light only explains a negligible part of the total effect.

The in-group favoritism channel

The 'in-group favoritism channel' captures a beneficial treatment of in-groups by the leader, in particular with respect to violence. Therefore, we first investigate whether the decrease in conflict intensity in autocratic leader regions is caused by a decrease in state violence or by a shift of conflict incentives of non-state actors. To do so, we divide the number of casualties into three categories: deaths related to state-based conflicts, deaths related to non-state-based conflicts and deaths resulting out of state attacks against civilians. State-based conflict events refer to conflicts between a government and another organized actor, whereas non-state-based conflicts refer to clashes between two non-governmental actors, such as rebel groups. We run separate regressions for each conflict type. The results are presented in table 3.5 and reveal that the reduction in conflict intensity is driven by fewer casualties in state-based conflict events. We previously hypothesized that leaders would use less violence against civilians in their home regions. The insignificant coefficients in column 3, however, do not support our hypothesis. Hence, we conclude that the decrease in conflict intensity in autocratic leaders' birth regions is mainly driven by state-based conflicts.

TABLE 3.5: In-group favoritism channel: types of conflict

	IHS(state casualties)	**IHS(non-state casualties)**	**IHS(civilian casualties)**
Leader autoc$_{t-1}$	-0.100**	-0.012	-0.013
	(0.045)	(0.022)	(0.029)
Leader non-autoc$_{t-1}$	-0.001	0.010	0.004
	(0.014)	(0.010)	(0.012)
Observations	1,177,805	1,177,805	1,177,805
R-squared	0.390	0.188	0.305

Note: The table reports OLS regression estimates of regressing the inverse hyperbolic sine function of the number of casualties categorized by type of conflict on the lagged indicators of autocratic and non-autocratic leader regions. Regression models as specified in table 4.2. *** p<0.01, ** p<0.05, * p<0.1.

Second, we analyze whether leaders mandate to install more security precautions in their home regions using Afrobarometer data. The use of Afrobarometer reduces our sample substantially. It covers 33–35 African countries.[4] The baseline effect cannot be replicated in this very restricted sample. Nevertheless, we believe that the additional analysis is helpful in understanding the channels of action. In the Afrobarometer surveys, enumerators are asked if they have seen any solider, policemen, their vehicles or a police station on their way to the specific survey location. We use this information as an indicator of military and police presence in the respective region and compare whether significantly more or less presence is reported in the home region of the leader compared to other regions in the country over time. Columns 1 and 2 of table 3.6 report the single items of army and police presence, whereas column 3 is a joint indicator of the presence of armed forces. The results in column 1 document that there is a higher likelihood of encountering a soldier or army vehicle in the birth region of an autocratic leader while the leader is in office than at other times. No significant difference is apparent for non-autocratic countries. In column 2, the results show less police presence in the birth regions of non-autocratic leaders and no significant difference in police presence in autocratic leaders' birth regions during the leader's time in office compared to other times. Hence, we conclude that there is some evidence supporting the hypothesis that autocratic leaders mandate the installment of more military in their home regions.

[4]We list them with the time of observation in table A.5 in the appendix.

TABLE 3.6: In-group favoritism: presence of armed forces

	(1) Army	(2) Police	(3) State force
Leader autoc$_{t-1}$	0.057*	0.033	0.041
	(0.033)	(0.067)	(0.036)
Leader non-autoc$_{t-1}$	-0.029	-0.099***	-0.076***
	(0.023)	(0.036)	(0.026)
Observations	6,682	6,686	6,686
R-squared	0.516	0.553	0.564

Note: The table reports OLS regression estimates of regressing index variables on the lagged leader region dummies. Outcome variables are based on the Afrobarometer rounds 1 to 6. Regression models as specified in table 4.2. *** p<0.01, ** p<0.05, * p<0.1.

The coup-proofing channel

The use of coup-proofing strategies to address internal threats may reduce violence in leader regions. As one coup-proofing strategy, leaders may engage in corruption to secure loyalty and minimize defection (Harm and Charap, 1999). Especially the armed forces' and the home regions' loyalty and support are crucial for maintaining political power. Anecdotal evidence indicates that leaders prefer assigning officers' positions to people from the own ethnic tribes and home regions, who are often less experienced and less interested in fighting (Lezhnev, 2016; Hashim, 2003). Hence, it is likely that conflicts of interests are settled by corruption instead of fighting. We compare citizens' perceived extent of political and police corruption over time using the Afrobarometer data. We would expect to see a higher degree of corruption in the birth regions of leaders during their time in office than at other time, if our hypothesis is valid. The results are reported in table 3.7. Column 1 shows the differential perceptions of political corruption between respondents in the birth region of the leader during office compared to prior and subsequent times, whereas column 2 reports perceptions of police corruption. Column 3 combines the two forms of corruption and provides a general measure of the perceived extent of public-sector corruption. The results show that citizens of autocratic leaders' birth regions perceive a higher level of political, police and public-sector corruption while the leader is in office. The effects are highly statistically significant and robust to the exclusion of single countries.

If political favoritism leads to fewer conflict in the home regions of autocratic leaders due to coup-proofing strategies, countries that are more likely to engage in such strategies should show a stronger effect of favoritism on conflict. We investigate heterogeneous effects along three dimensions.

First, we argue that the use of coup-proofing strategies depends on the perceived likelihood of an internal threat. Autocratic leaders may face a stronger internal threat if a coup happened in the country prior to their time in office. Therefore, we divide

TABLE 3.7: Coup-proofing channel: corruption

	(1) **Political corruption**	(2) **Police corruption**	(3) **Corruption index**
Leader autoc$_{t-1}$	0.186**	0.277***	0.240***
	(0.072)	(0.063)	(0.077)
Leader non-autoc$_{t-1}$	-0.092*	-0.023	-0.055**
	(0.047)	(0.042)	(0.023)
Observations	7,106	6,717	7,270
R-squared	0.643	0.674	0.677

Note: The table reports OLS regression estimates of regressing index variables on the lagged leader region dummies. Outcome variables are based on the Afrobaromter rounds 1 to 6. Regression models as specified in table 4.2. *** p<0.01, ** p<0.05, * p<0.1.

countries into countries that have ever and never experience a coup during the past 30 years. The results in column 1 of table 3.8 confirm our hypothesis. We find a negative and statistically significant effect on conflict of autocratic leader regions in countries with recent coup experience and no statistically significant effects of other leader regions. The home region of an autocratic leader in a country with at least one past coup attempt in the last 30 years experiences on average 16.1% fewer casualties during the leader's time in office.

Second, the use of corruption to reduce the willingness of the military to engage in coups, needs a financing source. Windfall gains, like the extraction of natural resources, provides a good possibility of rent-seeking. Hence, it appears likely that leaders of countries that are rich in natural resources are more likely to use bribing as a coup-proofing strategy compared to those with no natural resources (Girod, 2015). To test this hypothesis, we define a country to be rich in natural resources if a mine of the 14 major minerals exists in the country and classify countries into non-resource and resource-rich countries. Column 2 shows the heterogeneous effects of regional favoritism along this dimension. The results support the coup-proofing channel, showing that leader regions in autocratic regimes with natural resources experience fewer conflicts. No heterogeneous effect is found for non-autocratic leader regions.

Third, the granting of powerful positions to in-group members is more important in countries with existing polarization or segregation. We operationalize this by dividing countries along their ethnic fractionalization into less and more ethnically fractionalized countries at the median. As shown in column 3, we find a significant negative effect of autocratic leader regions in ethnically fractionalized societies but no significant effect of the other leader regions. Specifically, the home region of an autocratic leader in an ethnically fractionalized country experiences 18.9% fewer casualties during the leader's time in office. Hence, combining the evidence from all three coup-proofing regressions, we conclude that the reduction of conflict in home regions of autocratic leaders is likely to be driven by the use of coup-proofing strategies.

TABLE 3.8: Coup-proofing channel: heterogeneities

	IHS(casualties)		
	(1)	(2)	(3)
Leader autoc non-coup$_{t-1}$	-0.069		
	(0.052)		
Leader non-autoc non-coup$_{t-1}$	-0.005		
	(0.020)		
Leader autoc coup$_{t-1}$	-0.161**		
	(0.057)		
Leader non-autoc coup$_{t-1}$	-0.010		
	(0.042)		
Leader autoc non-resource$_{t-1}$		0.010	
		(0.037)	
Leader non-autoc non-resource$_{t-1}$		-0.009	
		(0.023)	
Leader autoc resource$_{t-1}$		-0.024***	
		(0.008)	
Leader non-autoc resource$_{t-1}$		0.100	
		(0.064)	
Leader autoc non-ethnic$_{t-1}$			0.046
			(0.056)
Leader non-autoc non-ethnic$_{t-1}$			-0.005
			(0.022)
Leader autoc ethnic$_{t-1}$			-0.189***
			(0.078)
Leader non-autoc ethnic$_{t-1}$			0.004
			(0.036)
Observations	1,177,805	1,177,805	1,089,755
R-squared	0.387	0.387	0.384

Note: The table reports OLS regression estimates of regressing the inverse hyperbolic sine of the number of casualties on the lagged indicators of (non-)autocratic leader regions. (Non-)autocratic leader regions are divided along three dimensions. First, into non-coup countries and countries with past coups, second, based on natural resources and third, based on ethnic fractionalization. A country is classified as ethnic if the ethnic fractionalization index is above the median and as natural-resource rich if it has at least one major natural resource deposit. Regression model as specified in table 4.2. *** p<0.01, ** p<0.05, * p<0.1.

3.7 Robustness checks

Our estimation strategy already captures many potential confounding factors with the country-year and region fixed effects. Nevertheless, regional time-varying factors can potentially bias our results. In the main analysis, we control for two kinds of local economic shocks and for population growth. In table 3.9, we provide three additional robustness checks. First of all, conflict and political decisions likely depend on past conflict events. To check whether our result is driven by pre-trends, we control for the share of past conflict years within the last three years. The results in column 1 of table 3.9 show that conflict events are positively correlated over time but the inclusion of past conflicts in the regression only marginally changes the estimates of the leader region indicators. Second, we include additional natural-resource shocks other than oil and gas as controls. For this purpose, we use the natural-resource information provided by Berman et al. (2017). The inclusion of 10 major minerals changes our regional favoritism effects on conflict intensity only marginally. Third, political trends like provincial independence efforts can influence election outcomes and potentially result in political violence. If this is the case, our estimation results so far are biased. We address this potential endogeneity with the inclusion of provincial time trends that control for average political developments and conflict dynamics in a province. Our results are robust to the inclusion of provincial time trends and very similar in magnitude compared to the baseline regression.

TABLE 3.9: Further controls

	IHS(casualties)			
	(1)	(2)	(3)	(4)
Leader autoc$_{t-1}$	-0.086*	-0.096**	-0.101**	-0.101**
	(0.044)	(0.040)	(0.043)	(0.044)
Leader non-autoc$_{t-1}$	0.007	0.011	-0.002	-0.007
	(0.017)	(0.015)	(0.018)	(0.017)
Past conflict		0.323***		
		(0.056)		
Observations	1,053,512	1,053,512	1,089,755	1,177,805
R-squared	0.413	0.440	0.384	0.429
Country-year FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Resource controls			Yes	
Provincial time trends				Yes

Note: The table reports OLS regression estimates of regressing the inverse hyperbolic sine of the number of casualties on dummies of (non-)autocratic leader regions. Regressions include fixed effects and control variables as indicated in the table. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

Attitudes and behavior towards the government may be more benevolent in the home region of the political leader compared to other regions in the country as they are in-group members with the leader. Coming from the same region and potentially sharing the same values and tradition, citizens of the home regions may feel more sympathetic towards the leader and have more trust in his/her government, reducing the likelihood of attacks or revolts against the leader in the home region. If this is the case, we would have falsely attributed the reduction in the intensity of conflict in the birth regions of autocratic leaders during the leaders' time in office to political favoritism. We analyze this potential bias by comparing the reported attitudes and behavior towards the leaders in their home regions during their time in office and prior or after that time. More precisely, we compare whether respondents of Afrobarometer surveys report to have more trust in the leader, are more likely to approve the performance of the leader and to be politically active when the region is the birth region of the current leader compared to other times. The results in table 3.10 show that persons residing in the birth regions of autocratic leaders do not report and evaluate the leaders differently than other citizens, once we control for region and country-year fixed effects. Only citizens in the home regions of non-autocratic leaders report to have more trust in their leaders. Hence, we find no difference in attitudes and behavior towards the government between regions in autocratic countries, validating our main results.

TABLE 3.10: Robustness check: change in perceptions

	(1) **Trust leader**	(2) **Performance leader**	(3) **Activism**
Leader autoc$_{t-1}$	-0.098	-0.195	0.071
	(0.166)	(0.192)	(0.044)
Leader non-autoc$_{t-1}$	0.160***	0.139	0.053
Observations	7,036	7,097	7,170
R-squared	0.746	0.728	0.817

Note: The table reports OLS regression estimates of regressing index variables on the lagged leader region dummies. Outcome variables are based on the Afrobarometer rounds 1 to 6. Regression models as specified in table 4.2. *** p<0.01, ** p<0.05, * p<0.1.

To examine the geographic scope of regional favoritism, we re-estimate our baseline result on a higher (the first) administrative level, which we refer to as provinces. The results are shown in table A.2. We estimate two distinct regression models. In column 1, we control for country-year and province fixed effects, whereas column 2 adds the control variables accounting for economic shocks at the provincial level. Throughout all regression specifications, we find no statistically significant coefficient. Yet, the magnitudes of the coefficients are comparable to our baseline regressions. This emphasizes that favoritism with respect to conflict has a rather local scope.

Lastly, we check whether the effect is driven by regime changes or irregular entries into office. Political transitions like the concentration of power to the leader can be accompanied by or achieved with political violence. In order to test whether the effect is driven by countries that recently switched from an autocratic or to an autocratic regime, we classify countries as switchers if there has been a change in the political system in the last five years and estimate a differential effect for these countries. The results are presented in column 1 of table A.3. We find no significant difference between well-established autocracies and countries that recently switched to an autocratic system in the regional favoritism effect on conflict.

Leaders, in particular autocratic leaders, may take over a country through violent means, potentially leading to an increase in conflict in the capital region. This rise in violence at the end or beginning of the time in office, may provoke a difference in conflict intensity between the home region of a leader and other regions in the country (including the capital region) that we would falsely interpret as a reduction of conflict in the home region. To check whether the effect is driven by these kinds of irregular entries into offices, we estimate heterogeneous effects between leaders that regularly or irregularly entered office as defined in the Archigos database. The results presented in column 2 of table A.3 show no differential effect of home regions of autocratic leaders that entered office irregularly compared to home regions of autocratic leaders with regular entrance.

3.8 Conclusion

In this study, we have investigated the effect of political favoritism on the occurrence and intensity of conflict in a global dataset of 172 countries. Using a region-year panel with information on 836 national leaders, our analysis extends the political favoritism literature by providing empirical evidence on a further dimension of favoritism namely with respect to conflict and security precaution. We combine geo-coded conflict information from the UCDP with data on the birthplaces and ethnic affiliations of political national leaders over the years 1989 to 2015. We include fixed effects along two dimensions (region and country-year) and controls for regional economic shocks and population density to estimate the causal effect of political favoritism on conflict. As politicians may shape the distribution of violence in various ways, we investigate the mechanisms of the effect. More specifically, we analyze three channels: the 'welfare channel', the 'in-group favoritism channel', and the 'coup-proofing channel'.

Our results show that political favoritism is not linked to the incidence of conflict but reduces the intensity of violence in the birth regions of autocratic leaders while they are in office. These regions experience around 10% fewer casualties during that time. We find no evidence for a reduction in conflict intensity in leaders' ethnic homelands, but ethnic groups that belong to the same ethnicity as the current leader are less involved in conflict. We identify two channels through which the effect occurs: the 'in-group favoritism channel' and the 'coup-proofing channel'. In leader regions fewer state-based casualties occur, potentially due to an increase in military presence. Moreover, in the leader regions, there is a higher extent of perceived public-sector corruption. This supports the anecdotal evidence showing that patronage in the allocation of officer positions leads to higher corruption and a change in behavior of the armed forces. Thus, this study also shows how state capacity and past coups determine conflict.

Chapter 4

Water scarcity and conflict

Joint work with Tilman Poser and Krisztina Kis-Katos

4.1 Abstract

Climate change, population growth and the increasing demand for water are altering the distribution of water in space and time. As water is key to life, water scarcity is likely to provoke social conflict. Using grid-cell data for Africa, Latin America, and the Caribbean over the years of 2002 to 2017, we establish a causal empirical link between the likelihood of local conflict and water mass declines. We measure water mass anomalies based on changes in Earth's gravity field recorded by GRACE and link them to social conflict events recorded in the SCAD data. To account for potential endogeneity in the demand for water, we instrument water mass change by the number of drought months per year. Our results show that drought-induced decreases in local water mass more than double the local likelihood of social conflict. The effect is substantially smaller in locations with access to groundwater. We find no robust differential effects by water demand factors.

4.2 Introduction

The massive rise in the demand for blue water in the agricultural and industrial sector starting in the 1950s, together with continuous population growth, have amplified water scarcity in several parts of the world. Climate-change induced increases in temperatures and in the frequency of extreme weather events may intensify the unequal distribution of water availability. As a result, water crises are often listed among the largest global risks for the future (e.g., World Economic Forum, 2020).

The global prevalence of water-related conflicts and crises is already quite substantial, highlighting the conflict inducing potential of the competition over scarce resources as proposed by Homer-Dixon (1994). International disputes over the use of Nile water reappeared with the construction of the Grand Ethiopian Renaissance Dam between Ethiopia, Sudan and Egypt in 2020. In India, numerous inter-state conflicts over state-crossing rivers have erupted in the past five decades (Richards and Singh, 2002; CNA, 2017). Violent clashes between herders and farmers in Nigeria resulted in more than 1300 deaths in 2018 and led to the displacement of thousands of people.[1] In 2013, protests against the government arose in Senegal, when the capital was running out of water due to a damage in the water pipeline.[2]

Beyond triggering conflict onset in its own right, water also plays a critical role in exacerbating already existing tensions. Longer periods without rainfall, combined with bad water management and rapid population growth, caused a surge in thirst- and hunger-related deaths in Yemen as around half of the population struggled to fulfill their basic daily water needs.[3] The increase in grievance and inequality contributed to the onset of the civil war.[4] Additionally, water stress is used as leverage in conflicts. During the ongoing Syrian civil war, violent extremist groups have captured major dams in order to increase pressure on the government and coerce the local population (CNA, 2017). These examples and many others suggest a causal link between water shortage and conflict.

Although empirical evidence on the direct link between water scarcity and conflict is limited, a substantial literature documents the effects of climatic shocks on violent conflict (Miguel et al., 2004; Ciccone, 2011; Hsiang et al., 2013; Burke et al., 2015; Harari and Ferrara, 2018). Yet, no consensus has been reached (Scheffran et al., 2012; Theisen et al., 2013). Given the wide range of the consequences of climate change, the

[1] Human Rights Watch (2018): Farmer-Herder Conflicts on the Rise in Africa, available at https://www.hrw.org/news/2018/08/06/farmer-herder-conflicts-rise-africa, accessed on 17.07.2020.

[2] Human Rights Watch (2013): Senegal seeks French, Chinese help as water crisis hits capital, available at https://www.reuters.com/article/us-senegal-water/senegal-seeks-french-chinese-help-as-water-crisis-hits-capital-idUSBRE98Q0MS20130927, accessed on 17.07.2020.

[3] Atlantic Council (2017): Running out of water: Conflict and water scarcity in Yemen and Syria, available at https://www.atlanticcouncil.org/blogs/menasource/running-out-of-water-conflict-and-water-scarcity-in-yemen-and-syria/, accessed on 17.07.2020.

[4] The Guardian (2015): Water scarcity in Yemen: the country's forgotten conflict, available at https://www.theguardian.com/global-development-professionals-network/2015/apr/02/water-scarcity-yemen-conflict, accessed on 17.07.2020.

controversial findings are not surprising. From the various channels through which climate change may trigger conflict, our paper focuses on increases in the local scarcity of water, which is an essential resource for livelihood. Couttenier and Soubeyran (2014) use the Palmer drought index as a measure of exposure to water stress and find a weak positive link between droughts and civil war in Sub-Saharan Africa. Almer et al. (2017) show that droughts, measured by the standardized precipitation and evapotranspiration index (SPEI), lead to a higher likelihood of conflict in Sub-Saharan Africa using a grid cell-month panel. They conclude that droughts are especially conflict-increasing in cells with higher water demand (high agricultural activity) and low water supply.[5] These studies provide important insights on the short-term effects of economic shocks arising out of relatively low rainfall, yet they fail to estimate the total and longer term effect of water scarcity, including hydrological droughts and the lack of water due to a misuse of resources. Additionally, they often neglect the capacity of groundwater to buffer rainfall anomalies.

We contribute to close this gap by providing empirical evidence on the direct link between reductions in water availability and conflict. Using a novel dataset that measures total water mass changes (at the surface as well as underground) at the grid-cell level, we are able to track water mass changes arising not only from rainfall anomalies but also from an overuse of water resources and groundwater droughts. We estimate the effect of a change in total available water mass within a grid-cell on the likelihood of conflict. Additionally, we identify which locations are the most affected ones based on time-invariant demand factors (capturing the presence of irrigation, mining activities and urbanization) and supply-side characteristics such as surface water and access to groundwater. By that, our paper also speaks to the literature investigating the mediator role of water supply characteristics in driving conflict (such as Döring 2020 and Sarsons 2015).

In order to establish a causal effect, we instrument water mass change by the number of drought months within each year derived from SPEI data (Croicu and Sundberg, 2015). The IV strategy rests on the assumption that the duration of a drought determines reductions in water mass and affects conflict incidence only through the channel of water availability. As the water supply of a location is determined by groundwater storage, rainfall, runoff and underground water flows, rainfall anomalies are an excellent predictor of changes in water mass. We argue that after controlling for cell and country-year fixed effects, the number of drought months is exogenous to the likelihood of conflict. In order to exclude other channels of causation (e.g., droughts being correlated with excessive temperatures that make people more violence-prone, Hsiang et al. 2013), further robustness checks control for variation in average temperatures and wind speed within each cell.

Our analysis combines satellite data on water mass movements at a 0.5 grid-cell level, provided by the Gravity Recovery and Climate Experiment (GRACE) mission from

[5] See Dell et al. (2014) for an overview of the literature.

US and German space agencies (NASA and DLR) (Wiese et al., 2018; Watkins et al., 2015; Landerer et al., 2020; Wiese et al., 2016) with geo-localized social conflict data from the Social Conflict Analysis Database (SCAD) (Salehyan et al., 2012). Changes in water mass are measured by deviations in the gravitation attraction of satellites circulating in Earth's orbit. We focus on social conflict as we believe that water scarcity directly provokes social disputes, and elaborate on the combined effect of water scarcity with already existing tensions by analyzing the effects on distinct types of conflict. Our dataset is a cell-year panel that consists out of 11,075 cells and covers Africa, Central America and the Caribbean, over the years 2002 to 2017.

The results show that a one standard deviation larger reduction in the water mass within a cell more than doubles the local likelihood of social conflict, increasing it from a baseline of 1% percent by 1.4 percentage points. The effect is substantially smaller in locations with access to groundwater. We find no evidence for stronger effects in locations with a higher water demand. Changes in water mass respond not only to current droughts but also to past droughts, emphasizing that studies that do not account for temporal dependencies may underestimate the magnitude of the effect of droughts on conflict.

The remainder of the paper is organized as follows. Section 2 describes the data and all measures used in the empirical analysis. Section 3 outlines the empirical strategy. Section 4 presents the empirical results and discusses issues of identification, while section 5 concludes.

4.3 Data, measurement and descriptives

4.3.1 Data and measurement

We combine data of water mass change at the grid-cell level with information on geo-referenced social conflict events to estimate the effect of water mass change on the likelihood of conflict. The analysis is at the cell-year level, whereby a cell refers to a resolution of 0.5 degrees (approximately 55 $\times$ 55 km). Our final panel dataset consists of 177,200 observations from 11,075 cells, located in 68 countries over the years 2002 to 2017. In our sample, the average yearly likelihood of a conflict is 1% per cell. The average cell experiences 3 drought months per year, and its mean yearly water mass change is about 0.55 centimeters of equivalent water thickness. Further descriptive statistics of the main variables are shown in table 4.1.

TABLE 4.1: Summary statistics

Variable	Mean	Sd	Min	Max	N
Social conflict	0.01	0.08	0.00	1.00	177200
Δ Water mass	0.00	1.00	-11.30	27.30	177200
Drought months	3.23	2.88	0.00	12.00	177200
Surface water	0.33	0.47	0.00	1.00	177200
Low groundwater depth	0.50	0.50	0.00	1.00	177200
Groundwater access	0.29	0.46	0.00	1.00	177200
Irrigation	0.26	0.44	0.00	1.00	177200
Urban	0.01	0.04	0.00	0.66	177200
Mining	0.07	0.26	0.00	1.00	177200
State target conflict	0.00	0.06	0.00	1.00	177200
Non-state target conflict	0.00	0.06	0.00	1.00	177200
Resource conflict	0.00	0.02	0.00	1.00	177200
Temperature	24.48	3.99	4.96	33.11	177136
Meridional velocity	0.11	0.95	-5.78	4.09	177200
Zonal velocity	-10.63	8.18	-32.41	13.92	177200

Conflict measures

Our main dependent variable measures *Social conflict* incidence and indicates whether a cell experiences at least one conflict event in a certain year. We use conflict event information from the Social Conflict Analysis Database (SCAD) (version 3.3) that reports social conflict events over the years 1990 to 2017, covering all of Africa, Mexico, Central America, and the Caribbean, with exact information on the location and time of each event (Salehyan et al., 2012). The dataset is unique in that it focuses on smaller scale social and local conflict events, which are more likely to be triggered by water shortage. Social conflict includes protests, riots, inter-communal conflict, and repression among others. It excludes large-scale conflict like civil wars, organized rebellions and international wars (Salehyan et al., 2012). The spatial distribution of the conflict events in figure 4.1 shows that social conflict is widely distributed across the geographical area of the sample, with two major conflict clusters in the North of Nigeria and another one in Tunisia.

To investigate which types of conflict are especially driven by water scarcity, we classify conflict events based on definitions of the SCAD dataset. First, we divide conflict events by their target into *State target conflict*, capturing conflict events targeting the central government, and *Non-state target conflict* that targets other actors. Second, we limit our attention to *Resource conflict*, defined as such if food, water, subsistence, or environmental degradation were mentioned as the first, second or third most important source of tension.

FIGURE 4.1: Distribution of conflict events

Note: The figure shows the location of conflict events during the sample period. Source: SCAD.

Water mass change

Our main explanatory variable is the change of water mass per grid cell and year, expressed in standard deviations. Water mass incorporates all kinds of water, including soil moisture, groundwater as well as surface water like rivers and lakes. Hence, it measures the change in total available water within a certain grid cell. To compute this measure, we rely on a novel data source that records water mass movements based on satellite data for the years 2002 to 2017. More specifically, we use the processed GRCTellus JPL Mascon monthly mass grid dataset (release 6) that is based on observations of global mass flux gathered by the Gravity Recovery and Climate Experiment (GRACE) mission from US and German space agencies (NASA and DLR) (Wiese et al., 2018; Watkins et al., 2015; Landerer et al., 2020; Wiese et al., 2016).

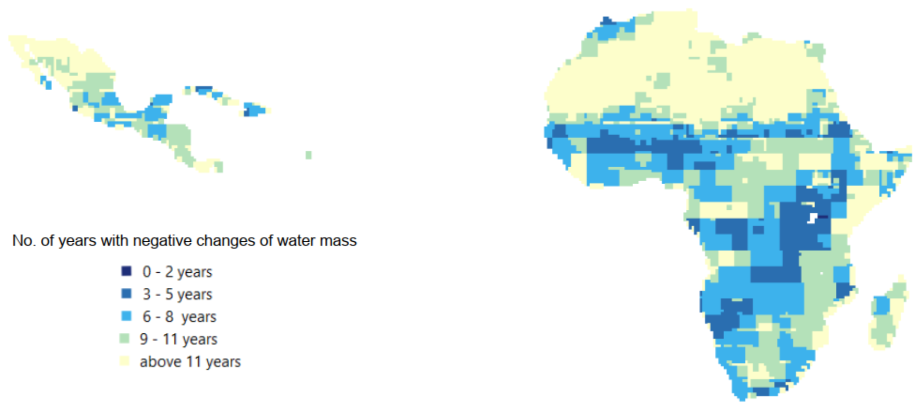
Water mass changes are measured by the small changes in the distance between two satellites that follow each other in orbit when circulating around the Earth. The small changes arise out of shifts in the Earth's gravity field. Less water mass on Earth results in a weaker gravity field, whereas more water mass leads to a stronger gravity (Cooley and Landerer, 2019). The Mascon processing procedure uses geophysical constraints on the regional level to filter out noise and does not need further de-striping algorithms or smoothing, like traditional spherical harmonic gravity solutions do (Watkins et al., 2015).[6] Additionally, a Coastal Resolution Improvement (CRI) filter is applied to the data. The processed data records water mass anomalies of each month with respect to the time average of 2004 to 2009 at the 0.5 degree grid-cell level in equivalent water mass thickness in centimeters. However, it is important to note that the native resolution of measurement is at the 3 degree grid level. Therefore, we cluster standard errors at that level to allow for the interdependence of measurement. Gain factors derived from a CLM hydrological model are applied to the data to

[6]For a detailed description of the processing procedure see Watkins et al. (2015) and Wiese et al. (2016).

extrapolate the GRACE estimates from their effective spatial resolution to the finer spatial scale. As these factors are much closer to a resolution of 1 for the spherical harmonic gravity solutions, we provide additional regressions at the 1 degree level as a robustness check. This novel dataset has been validated with other data sources (Scanlon et al., 2016; Chambers and Bonin, 2012; Klosko et al., 2009).

We aggregate the data on a yearly level by taking the average over all months in a year. Figure 4.2 depicts the spatial distribution of negative changes in water mass in our sample. It shows that the decline in water mass visibly varies in our sample area, and that there are geographical clusters. The Northern part of Central America and the Sahel-region experienced water declines in almost all years of the sample period, whereas Burundi and Rwanda experienced only few years of water reduction.

FIGURE 4.2: Distribution of water decline

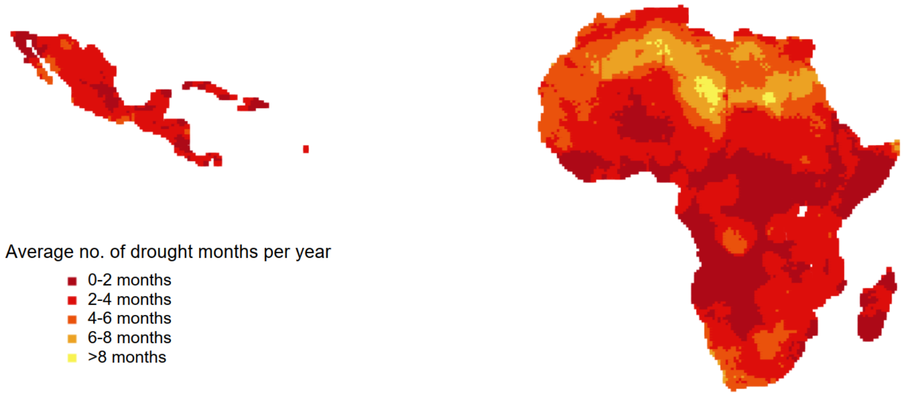


Note: The figure reports the number of years with negative changes in water mass. Source: GRACE Tellus and FO, Nasa and DLR.

Drought months

In our empirical analysis, we instrument the change in water mass by the duration of drought measured by the number of drought months within a year. We base our drought indicator on the standardized precipitation and evapotranspiration index from the SPEIbase (version 2.5), computed at a 3-month scale. The SPEIbase reports monthly information on drought conditions at a 0.5 grid cell resolution. It measures precipitation anomalies by a standardized z-score that is based on monthly precipitation and potential evapotranspiration information provided by the Climatic Research Unit of the University of East Anglia (Vicente-Serrano et al., 2010). We define a month to be affected by a drought if the SPEI value is below -1 in a given grid cell and count the number of months with drought per year. The spatial distribution of average drought months per year is shown in figure 4.3. During our sample period, Central Africa has been less affected by droughts than North Africa where droughts were pervasive, with an average of more than 6 drought months per year. The majority of cells located in Central America experienced on average 2 to 4 months of droughts per year.

FIGURE 4.3: Distribution of droughts



Note: The figure reports the average number of months with SPEI values below -1 per year during the sample period 2002 - 2017. Source: SPEIbase.

Demand and supply factors

In the heterogeneity analysis, we investigate differential effects of water mass change on conflict by interacting them with time-invariant measures of water supply and demand. As supply factors we consider the availability of surface water and access to groundwater. We define a cell to hold *Surface water* if a river or lake is located within the respective cell. Information on the geographical location of rivers and lakes is taken from the river and lake centerlines map (version 4.1) provided by (Natural Earth, 2020). *Groundwater access* is an indicator variable that combines information on groundwater storage and depth to groundwater. We define a cell as having access to groundwater if two conditions are fulfilled at the same time: it is part of a high groundwater storage area and the depth to groundwater is low. Information on groundwater storage is taken from the Groundwater Resources of the World database (WHY map BGR version 1.0) provided by the World-wide Hydrogeological Mapping and Assessment Programme. It classifies groundwater sources based on the geological components of the aquifer in three categories: major groundwater basin, complex hydrological structure and shallow and local aquifer. Based on this information, we define a cell as having high groundwater storage if its groundwater source is classified as a part of a major groundwater basin or of a complex hydrological structure (Richts et al., 2011). Information on the depth until reaching groundwater is taken from Fan et al. (2013). Their map gives water table depths in meters below land surface at a 1 km grid resolution. The map is constructed by integrating over 1 million data points measured at well sites into a groundwater model. We aggregate the information to a 0.5 degree resolution and divide locations along the median (approximately 25 mbgl). Based on these definitions, around 30% of our sample has access to groundwater.

With around 70% of total water use, agriculture is the far biggest consumer of water in the world (Siebert et al., 2013). In agriculture, water is mainly used to irrigate crops.

Therefore, we operationalize agricultural water demand by identifying areas that are irrigated. We base our measure on the global irrigated area map (GIAM) provided by the International Water Management Institute (IWMI) (Thenkabail et al., 2009). Using satellite images, the map identifies irrigated areas in 2000 at a 10 km resolution. Based on these data, we construct the indicator variable *Irrigation* that takes the value of one if an irrigated area is located in a cell. 30% of the grid cells in our sample have irrigated areas.

Mining is another sector that can heavily rely on water. Water is needed for a broad range of activities in the mining process such as mineral processing and dust suppression (Garner et al., 2012). We use the major mineral deposits of the world dataset provided by U.S. Geological Survey (Schulz and Briskey, 2005) in combination with the global-scale data set of mining areas to identify locations with mining potential (Maus et al., 2020). The USGS dataset provides the geographical location of deposits of major non-fuel mineral commodities whereas the latter dataset identifies mining areas using satellite images. Based on this information, we define a cell as potentially active in *Mining* if at least one major known mineral deposit or a mining area is present in the cell.

Water consumption increases with population size. Therefore, as a third water demand factor, we distinguish grid cells based on their population size. We rely on the Urban Extents Grid database provided by the Socioeconomic Data and Application Center (SEDAC) that differentiates urban and rural areas based on population size, settlement areas, and the presence of nighttime lights. On a 30 arc second resolution, urban areas are identified by connected lighted cells or settlement points for which the total population is greater than 5,000 persons (SEDAC, 2011; Balk et al., 2006). We aggregate the data to the 0.5 degree resolution and define cells with any urban area as *Urban*.

Atmospheric factors

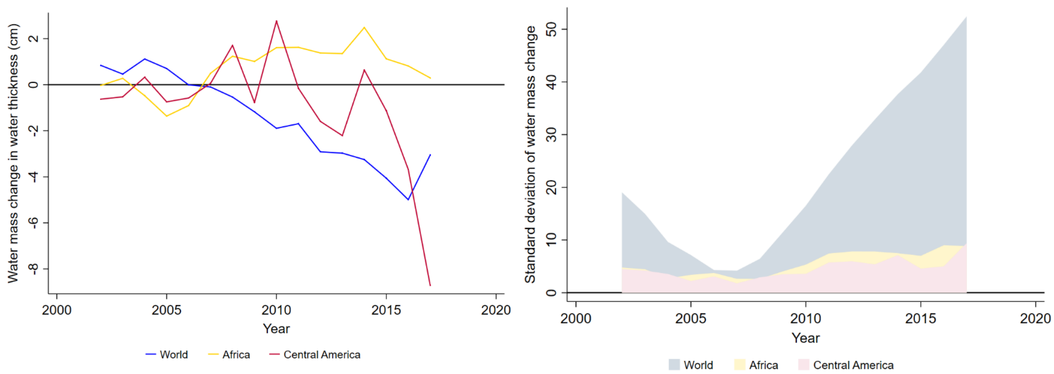
As a robustness check, we control for two atmospheric factors potentially threatening the exclusion restriction of our instrument. We control for average *Temperature* per year in a cell and two dimensions of wind speed. We rely on monthly averages provided by the NCEP/NCAR 40-year reanalysis project from the Physical Science Laboratory (PSL) that processes daily data on wind speed and temperature from the National Center for Environmental Prediction (NOAA) (Kalnay et al., 1996). Temperature data are reported in degree Celsius, whereas wind speed is measured as *Zonal wind velocity* and *Meridional wind velocity*. Zonal wind velocity measures the wind speed in meter per second in the west-east direction, whereas meridional wind velocity captures wind speed in north-south direction. We separate wind speed by direction because the direction of the wind flows is associated with different meteorological conditions. Meridional flows tend go along with extreme weather events, whereas zonal wind is connected to quiet weather conditions (Milrad, 2017).

We aggregate the data to the spatial resolution of 0.5 degrees and to a yearly level by taking averages.

4.3.2 Temporal trend in the change of water mass

The novel dataset on water mass change enables us to observe how water movements change over time. The left panel of figure 4.4 presents the average water mass change in equivalent water mass thickness in centimeters over the sample period of 2002 to 2017 (compared to the time average of 2004 to 2009). It reports average water mass change for the whole world as well as for the two continents included in our conflict data sample, Africa and Central America combined with Mexico. The right panel of figure 4.4 shows how the standard deviation of water change developed over time.

FIGURE 4.4: Change of water mass over time



Note: The figure reports the average water mass change over the years 2002–2017. Water includes all kinds of surface and underground water. Source: GRACE Tellus and FO, Nasa and DLR.

On a global level, the data depicts the expected patterns associated with climate change and the increased demand for water. On the one hand, the change in water mass follows a strongly negative trend, with larger water mass declines in later years. On the other hand, the spatial variation in water mass change has substantially increased since 2006, reflecting the more unequal distribution of rainfall in the world. This highlights that localized water scarcity is likely to become more prevalent in the future.

Within our chosen geographical area, we see two distinct trends. Water mass change in Central America follows a negative trend that is broadly similar to the global one. However, it strongly surpasses the global declines by the end of our time period. By contrast, average water mass in Africa has increased over the last decade. In both areas, the variation of water mass change has substantially increased over time. It is also evident that some locations are more affected by water decline than others (see figure 4.2 and the description above). The following empirical analysis will utilize this spatial and temporal variation of water mass change to infer the effect of change in water mass on social conflict.

4.4 Empirical strategy

In order to estimate a causal effect of change in water mass on conflict incidence, we apply an instrumental variable approach, using the temporal and spatial variation of negative rainfall shocks. Our baseline estimation model is defined as follows:

$$\textit{Social conflict}_{ict} \quad = \quad \beta\, \Delta \textit{Water mass}_{ict} + \alpha_{ct} + \mu_i + \epsilon_{ict}, \tag{4.1}$$

where $\textit{Social conflict}_{ict}$ is an indicator variable that takes the value of one if a social conflict event occurred in year t and grid cell i, located in country c. Δ $\textit{Water mass}_{ict}$ measures the change of water mass in standard deviations in the respective year and cell. Throughout all estimations, β is the coefficient of interest, measuring the effect of local water mass change on the likelihood of conflict. In all estimation models, standard errors are robust and clustered at the 3 degree grid-cell level to account for the native resolution of measurement of water mass change.

The regressions include cell fixed effects, μ_i, combined with year or country-year fixed effects, α_{ct}. Cell fixed effects control for all time invariant differences, absorbing spatial differences in average changes of water mass and the propensity to experience conflict. Year fixed effects absorb major shocks, such as global economic crises or El Niño years. Country-year fixed effects, which we use in our preferred specifications instead, account for more idiosyncratic yearly variation in the national water management system, climatic conditions, as well as of country-wide political, social and economic shocks.

A remaining endogeneity problem arises as local changes in water mass are not random but also reflect variation in water demand by the local population. For instance, a massive immigrant inflow may increase local water demand, resulting in a decline of water mass, and at the same time provoke conflict (Brückner, 2010). This would lead to a spurious negative correlation between water availability and conflict. Alternatively, positive income shocks due to an increase in commodity prices may lead to a higher demand for water (due to more irrigation) but also increase the opportunity costs of social unrest (Dube and Vargas, 2013), potentially biasing a true negative relationship between changing water availability and conflict towards zero.

To deal with these endogeneity concerns, we instrument the change in water mass by a measure of exogenous weather shocks that drive local water availability: the number of drought months in the respective year and cell. Our second stage regression remains as described by equation eq:model, but it is extended by a first stage that takes the following form:

$$\Delta\, \textit{Water mass}_{ict} \quad = \quad \theta\, \textit{Drought months}_{ict} + \alpha_{ct} + \mu_i + \epsilon_{ict}, \tag{4.2}$$

and includes both cell fixed effects, μ_i, and year or country-year effects, α_{ct}.

The empirical strategy rests on the assumption that the duration of drought determines the change in local water mass and affects the incidence of violent conflict only through this channel. Apart from groundwater storage, runoff and underground water flows, rainfall is the main determinant of local water supply. Hence, rainfall anomalies provide an excellent instrument for water mass change. Rainfall anomalies have been widely used in the conflict literature as an instrument for economic shocks in developing countries (Miguel et al., 2004; Ciccone, 2011; Harari and Ferrara, 2018). These studies argue that in agriculture-based economies, the lack of rainfall reduces crop yields (because of water scarcity), acting as an economic shock. Our approach follows this argument, yet we also emphasize that a change in water availability may affect conflict directly as well, for instance because of arising water right disputes or civil unrest. The drought instrument provides a local average treatment effect (LATE) by isolating the effect of water mass change that is induced by exogenous weather shocks.

We argue that conditional on cell and country-year fixed effects, the number of drought months is exogenous to conflict incidence. Whereas the number of rainfall anomalies varies across climatic zones and with geographical factors like terrain or elevation, and the local susceptibility to climatic change (which potentially also affects the likelihood of conflict (Breckner and Sunde, 2019)), the spatial and temporal distribution of rainfall deviations within a grid cell and year is as good as random.

A final concern arises with respect to the exclusion restriction of the instrument as droughts may be correlated with other atmospheric factors, like temperature or wind, which can affect conflict directly. For instance, heat may trigger aggressive behavior (Anderson, 1989), while at the same time, it is likely to accompany droughts. Heavy wind speed can disrupt economic activities (Nelson, 2010; Slettebak, 2012), while being correlated with the occurrence of precipitation (Waliser and Guan, 2017). If rainfall anomalies are closely linked to such atmospheric factors, we falsely attribute their effect to that of localized droughts. By that, we would overestimate the effect of water scarcity on conflict. We address this concern in a robustness check in which we control for the two main atmospheric factors, including *Temperature* and *Zonal* and *Meridional wind speed* as control variables in both stages of our regressions.

4.5 Results

4.5.1 Baseline results

Table 4.2 reports our baseline results from regressing the incidence of social conflict on the change of water mass, conditional on fixed effects. Columns 1 and 2 show OLS estimates, whereas columns 3 and 4 present our preferred specifications in which the change in water mass is instrumented by the number of drought months of the respective year. In odd columns, the models include cell and year fixed effects. The even columns present models with cell and country-year fixed effects, which are even more restrictive. The OLS results in columns 1 and 2 show no significant correlation between a change in water mass and conflict after controlling for time-invariant cell characteristics and global or nation-wide temporal shocks. The OLS results are most likely biased though, as water mass change responds strongly to economic and political factors influencing water demand and conflict at the same time.

TABLE 4.2: Baseline results

Dependent variable		**Social conflict**		
Model	OLS		IV: Second stage	
	(1)	(2)	(3)	(4)
Δ Water mass	-0.000	0.000	-0.008***	-0.014*
	(0.000)	(0.000)	(0.003)	(0.008)
Dependent variable			**Δ Water mass**	
Model			IV: First stage	
Drought months			-0.045***	-0.020***
			(0.006)	(0.004)
Kleibergen-Paap F stat			49.11	24.01
Stock-Yogo critical value 10%			16.38	16.38
Observations	177,200	177,200	177,200	177,200
Cell FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
Country-year FE		Yes		Yes

Note: The table reports OLS and IV coefficient estimates of an indicator variable for social conflict on the change of water mass within each cell. Models include fixed effects as stated in the table. Robust standard errors are clustered at the 3 degree cell level.

We address the potential endogeneity concern by instrumenting the change of water mass by the number of drought months. The first stage results show a highly significant effect of drought months on the change in the local water mass. The significant effect and the high Kleinbergen-Paap F-statistic (49.1) confirm the relevance of our instrument. Conditional on cell and year fixed effects, a further drought month is estimated to induce a 0.045 standard deviations stronger decline in water mass. The effect is significant at the 1% level. The more restrictive model, including cell and country-year fixed effects (column 4), factors out large-scale climatic shocks that affect whole countries. It relies on within country variation in drought months only. In this specification, the effect decreases to 0.02 standard deviations. Its statistical significance remains high. At the second stage, the IV results show a negative and significant relationship between shifts in the water mass and conflict years. Controlling for cell and year fixed effects, a one standard deviation larger decrease in the local water mass increases the likelihood of social conflict by 0.8 percentage points. Conditional on cell and country-year fixed effects, this effect increases to 1.4 percentage points. With an average yearly likelihood of conflict of 1%, the effect is substantial as one standard deviation lower change in water mass more than doubles the local likelihood of conflict.

We conclude that changes in water availability, induced by exogenous variation in the local duration of drought, shape the likelihood of conflict. Yet, we find no correlation between change in water mass and conflict in the OLS setting, indicating that the OLS estimates are biased upward. This suggests that increases in water demand go along with factors reducing the likelihood of conflict. For instance, water demand is likely to rise during economic upturns, e.g. when the local population is better able to purchase additional water resources from other locations. At the same time, economic growth reflects higher opportunity costs to fight. An alternative interpretation of the results is that drought-induced changes in water mass have a different effect as compared to changes in water mass caused by a higher water demand. We will explore the differential effects by water demand and supply factors next. In what follows, we will only focus on our more restrictive IV model from column 4 of table 4.2 that includes both cell and country-year fixed effects.

4.5.2 Heterogeneous effects by supply and demand factors

Water scarcity arises when local water demand exceeds the current water supply. It can result out of a higher demand of water, a lower supply of water or a combination of both. Around the globe, water supply varies strongly. Whereas some regions are equipped with large and persistent groundwater storage, reducing their susceptibility to rainfall shocks and water demand shocks, other regions lack such a buffer and are more vulnerable to shifts in water demand or supply. Yet, even if groundwater storage is high, it may be unreachable for the local population if it is situated deep underground. Hence, we expect heterogeneous effects of changes in water mass on conflict depending on the local accessibility and amount of water.

Columns 1 and 2 in table 4.3 present the heterogeneous effects of water mass change on conflict by supply factors. We investigate the heterogeneity by estimating the differential effect of drought in water-rich as compared to water-poor locations. Therefore, we include an interaction term of water mass change and the respective time-invariant supply factor in the regression as second, potentially endogenous, explanatory variable. To deal with the additionally arising endogeneity, we add the interaction of drought months with the respective supply factor as a further instrument to both first stages. In table 4.3 we report only the first stage for water mass change and suppress the first stage for the interaction. Column 1 presents results differentiated by the availability of surface water and column 2 by access to groundwater. First stage results show that drought months reduce the measured water mass substantially more in places with surface water compared to locations without surface water (column 1). We find no significant difference in the effect of drought on total water mass change in places with a better or worse access to groundwater (column 2). Taken together, the two sets of results indicate that water mass at the surface varies more strongly with drought than the one underground.

The second stage results show no significant difference in the effect of water mass change on conflict depending on the presence of surface water (column 1). But, the effect varies significantly with access to groundwater. In cells with an easier access to groundwater, a standard deviation larger decrease in water mass increases the likelihood of conflict by 0.6 percentage points only as compared to 1.8 percentage points in case of inaccessible groundwater. Consequently, local access to abundant groundwater can act as a buffer of climatic shocks, substantially reducing the effect of drought shocks on conflict.

TABLE 4.3: Heterogeneous effects by water demand and supply factors

Dependent variable			**Social conflict**		
Interacted factor	**Surface water**	**Groundw. access**	**Irri-gation**	**Mining**	**Urban**
Model			IV: Second stage		
	(1)	(2)	(3)	(4)	(5)
Δ Water mass	-0.017**	-0.018**	-0.021**	-0.016**	-0.015*
	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
× Interacted factor	0.006	0.011*	0.014**	0.009	0.031
	(0.005)	(0.006)	(0.006)	(0.006)	(0.066)
Dependent variable			**Δ Water mass**		
Model			IV: First stage		
Drought months	-0.018***	-0.019***	-0.017***	-0.020***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
× Interacted factor	-0.013**	-0.005	-0.012*	-0.007	-0.139*
	(0.004)	(0.007)	(0.005)	(0.009)	(0.055)
Kleibergen-Paap F stat	12.08	12.15	10.27	12.16	10.67
Observations	177,200	177,200	177,200	177,200	177,200

Note: The table reports IV coefficient estimates of the incidence of social conflict within each cell on the change of water mass and interactions with supply and demand side factors. The interactions of water change and the various supply and demand factors are instrumented by drought months and the interaction of drought months with the respective factor (the latter first stage is not reported here). Surface water measures the presence of rivers or lakes within the cell; groundwater access indicates low depth to groundwater and high groundwater storage; irrigation indicates the presence of any irrigated area within the cell; mining indicates the presence of major mineral deposits; urban marks cells with urban areas. The models include cell and country-year fixed effects (see column 4 of table 4.2). The Stock and Yogo critical value for a 10% bias is 7.03 in all regressions. Standard errors are clustered at the 3 degree cell level.

Like water supply, water demand is distributed unevenly in space. Accounting for around 70% of the total water demand, agriculture is the main water consumer in the world (Otto and Schleifer, 2020). Additionally, water demand is higher in more populated areas and in locations where water-intensive industries are located such as mining and energy production (Otto and Schleifer, 2020). The pivotal role of water in these areas leads us to hypothesize that the effect of water mass change on conflict is stronger in locations with higher water demand compared to locations with lower water demand.

We analyze the heterogeneous effects by water demand focusing on the wide-spread prevalence of irrigation, the potential presence of mining and urbanization. The demand factors enter the regression in the form of interactions, similar to the supply factors above. Column 3 in table 4.3 presents the results for irrigation, column 4 for mining, whereas column 5 shows the heterogeneous effects by urbanization. In the first stages, we estimate a stronger reduction in water mass in the aftermath of drought both in irrigated and urbanized areas compared to non-irrigated and less urbanized areas. We find no differential effect by mining potential. These results indicate that during drought even more water is consumed in economically more advanced rural as well as in more urbanized areas.

Surprisingly, the second stage results show a weaker increase in conflict with declines in water availability in irrigated areas compared to non-irrigated areas. We find no differential effects by mining activities or urbanization. A potential explanation of the weaker effect in irrigated areas is the strategic location of irrigated agricultural production in areas with groundwater access, which hampers a clean distinction between the effects of irrigation and groundwater access. Overall, the results do not confirm our hypothesis. They indicate that although water demand factors accelerate water scarcity, they do not intensify the effect of water mass change on conflict.

4.5.3 Robustness checks

In our main analysis, we focus on social conflict. Yet, apart from social disputes over a scarce resource and its fair distribution, water scarcity may exacerbate already existing grievance, decreasing the opportunity costs to fight and increasing the possibilities of rebel groups to recruit new members. Moreover, rebel groups can strategically damage and capture water infrastructure in order to increase pressure on the population and government, advancing their goals (CNA, 2017). Additionally, water scarcity may provoke political unrest, holding the government accountable for bad water management. Governments may be expected to control both water demand and supply. On the one hand, governments can limit water demand by regulating water-intensive industries and establishing water-use policies. On the other hand, they can improve the water supply by investing in water infrastructure. For instance governments can invest in the construction of dams or water reservoirs, waste water management, and in facilitating access to groundwater sources.

In order to analyze what types of conflict are caused by water scarcity, we classify the SCAD conflict events into conflict events targeting the state and non-state actors. Additionally, we analyze resource conflict by focusing on those conflict events that were explicitly listed as arising out of tensions dealing with water, food, subsistence, and environmental degradation. The results are reported in table 4.4, which shows that the conflict inducing effects of water declines are driven by conflict events targeting the state but not those that are targeting other actors. Civil unrest, demonstrating dissatisfaction with the government, is a major factor driving the effect of water mass change on the likelihood of conflict in our study. Surprisingly, the results show no effect of water mass change on resource conflict. However, this null result is most likely driven by a lack of power (and a potential for mis-reporting) as out a total of 1133 conflict occurrences at the cell-year level only 71 are classified as resource conflict.

TABLE 4.4: Types of conflict

Dependent variable:	**State target conflict**	**Non-state target conflict**	**Resource conflict**
Model:		IV: Second stage	
	(1)	(2)	(3)
Δ Water mass	-0.011**	-0.003	-0.002
	(0.005)	(0.005)	(0.001)
Dependent variable:		**Δ Water mass**	
Model:		IV: First stage	
	-0.020***	-0.020***	-0.020***
	(0.004)	(0.004)	(0.004)
Observations	177,200	177,200	177,200
Kleibergen-Paap F stat	24.01	24.01	24.01

Note: The table reports IV coefficient estimates of various types of conflict on water change. State target conflict refers to conflicts that targeted the government and non-state target conflict the rest of the conflicts. Resource conflicts are conflicts about water, food, subsistence of environmental degradation. Models include cell and country-year fixed effects. Robust standard errors are clustered at the 3 degree grid cell level.

The exclusion restriction of our instrumental variable approach might not hold if atmospheric factors, which enter our drought measures through the estimation of evapotranspiration, affect conflict directly. In order to account for this second channel, we include two main atmospheric factors, temperature and two measures of wind speed, as control variables in the regression. The results are presented in table 4.5. At the first stage, we see the expected relationship between water mass change and atmospheric conditions. Higher temperatures go along with larger decreases in water mass. Zonal wind speed (measuring wind flows from west to east or vice versa) is not related to changes in the water mass, but meridional velocity, which is associated with extreme weather trends (Milrad, 2017), is negatively linked to water mass change. At the second stage, the inclusion of the additional control variables leads to at most marginal changes in the effect of water mass change on conflict. Thus, the results fully support the validity of our empirical strategy. With respect to the atmospheric factors, the results show ceteris paribus no significant relationship between conflict and average temperatures or wind speed.

TABLE 4.5: Additional controls

Dependent variable	**Social conflict**		
Model	IV: Second stage		
	(1)	(2)	(3)
Δ Water mass	-0.016*	-0.014*	-0.016*
	(0.008)	(0.008)	(0.008)
Temperature	-0.002		-0.002
	(0.001)		(0.001)
Meridional velocity		-0.000	-0.000
		(0.001)	(0.001)
Zonal velocity		-0.000	-0.000
		(0.000)	(0.000)
Dependent variable	**Δ Water mass**		
Model	IV: First stage		
Drought months	-0.018***	-0.020***	-0.018***
	(0.004)	(0.004)	(0.004)
Temperature	-0.112***		-0.114***
	(0.026)		(0.026)
Meridional velocity		-0.052**	-0.058**
		(0.020)	(0.020)
Zonal velocity		0.005	0.004
		(0.003)	(0.003)
Kleibergen-Paap F stat	19.93	24.03	19.97
Observations	177,136	177,200	177,136

Note: The table reports IV coefficients of social conflict on water mass change controlling for atmospheric factors. Models include cell and country-year fixed effects. Robust standard errors are clustered at the 3 degree grid cell level.

A decrease in rainfall will directly reduce water availability at the surface, but it also has a retarded effect on groundwater recharge and groundwater levels, triggering a groundwater drought (Han et al., 2019). The delay depends on the speed of water movements, which is determined by geological and geographical characteristics (Han et al., 2019). If a population relies mainly on groundwater sources, the retarded effect may have a stronger impact on their behavior than the immediate one. Hence, past water mass change may contribute to conflict, too.

To investigate the temporal dynamics, we include temporal lags of the explanatory variables in our models. Table 4.6 presents the results. Column 1 shows the baseline regression for the shorter sample period, column 2 includes the first temporal lag of drought months, whereas column 3 includes temporal lags for both drought months and water mass change. The reduction in the sample period only marginally changes the estimated coefficients. A one standard deviation larger water mass reduction increases the likelihood of conflict by 1.8 percentage points as compared to 1.4 percentage points in the main sample (cf. table 4.2). Column 2 includes the temporal lag of drought months as an additional instrument, whereas in column 3 past water mass change is added to the second stage to measure the delayed effect of water scarcity. In this latter specification, past water mass change is instrumented by past drought months. The first stage results in both columns report that drought indeed has a cumulative effect on water mass change over time. The duration of drought in the previous year magnifies the decrease in water mass in the current year. The second stage estimates of water mass change on conflict stay of a broadly comparable magnitude throughout all three specifications. In column 3, the temporal lag of water mass change is not significant. The weak instrument tests also show F-statistics that lie below the critical values for a 10% potential bias in the IV estimates and indicate that these dynamic results should be interpreted with more caution than our baseline model. Nonetheless, the first and second stage results indicate that droughts have a longer-lasting effect on conflict due to their cumulative effects on water availability. Only current water mass decline seems to induce conflict, while conditional on the current decline, past fluctuations in water availability do not result in more conflict at the present time. Past droughts matter because of their longer lasting effects on water availability, whereas water availability has only an immediate effect on the likelihood of conflict.

TABLE 4.6: Time dynamics

Dependent variable		**Social conflict**	
Model		IV: Second stage	
	(1)	(2)	(3)
Δ Water mass	-0.018*	-0.014*	-0.015*
	(0.009)	(0.008)	(0.008)
Δ Water mass$_{t-1}$			0.007
			(0.006)
Dependent variable		**Δ Water mass**	
Model		IV: First stage	
Drought months	-0.018***	-0.016***	-0.016***
	(0.005)	(0.004)	(0.004)
Drought months$_{t-1}$		-0.010***	-0.010***
		(0.003)	(0.003)
Kleibergen-Paap F stat	15.76	8.573	6.813
Stock-Yogo critical value 10%	16.38	19.93	7.03
Observations	166,125	166,125	166,125

Note: The table reports IV coefficient estimates of social conflict on present and past changes in water mass at the cell level. Water mass change is instrumented by the number of past and present drought months. Models include cell and country-year fixed effects. Robust standard errors are clustered at the 3 degree grid cell level.

As a final step, we investigate the sensitivity of our results to the spatial resolution used in the analysis. Our outcome variable, the incidence of social conflict, and our instrumental variable, the number of drought months, are both measured at the 0.5 degree resolution. This allows us to establish a precise geographical link between local climatic factors and specific conflict events. However, the main explanatory variable, the change in water mass, is only spatially modelled (extrapolated) to a level between 0.5 and 1 degrees. Its precise measurement is based at the 3 degree resolution. We have addressed the spatial interdependence of the changes in water mass that were caused by the higher level of original measurement by clustering the standard errors at the 3 degree level throughout our analyses. This takes into account all potential correlation between the error terms that is induced by measurement errors within the 3-degree grid cell. Alternatively, we re-run the baseline regression on the 1 degree grid-cell resolution to analyze the sensitivity of our estimates to our selection of the spatial resolution. The results are reported in table B.1. Column 1 presents the estimates of the model using cell and year fixed effects and column 2 shows the results of our main specification with cell and country-year fixed effects. In both regression models, we find a negative and significant effect of change in water mass on conflict, validating our main results. As shown in column 2, the magnitude of the effect more than doubles compared to our baseline regression estimate (3.8 percentage points compared to 1.4 percentage points), increasing the average likelihood of conflict at this resolution from 1.3% to 5.1%. This indicates that the higher spatial resolution may result in more measurement error and bias our estimated coefficients towards zero.

4.6 Conclusion

Due to the ongoing climate change and a globally rising demand for water, the consequences of water scarcity have been gaining policy importance. In this paper, we assess the effects of changing water availability on conflict at the local level. In a cell-year panel covering Africa, Central America and the Caribbean over the years of 2002 to 2017, we estimate the effect of changes in the total available water mass on the likelihood of conflict. For this purpose, we combine novel satellite data on water mass movements, provided by the Gravity Recovery and Climate Experiment (GRACE) mission from US and German space agencies (NASA and DLR), with social conflict events from the Social Conflict Analysis Database (SCAD). In order to establish a causal effect of water mass change on conflict, we implement an instrumental variable approach, instrumenting changes in total water mass by the number of drought months per year, based on the SPEI.

Our estimates reveal the total effect of a reduction in local water mass on conflict, resulting from rainfall shocks, less runoff but also groundwater depletion. Thus, we contribute to the literature by not only focusing on the effects of drought shocks in a reduced form, but linking social conflicts to their true driver, the worsening access to water that is a vital natural resource. Our results show that a reduction in total water mass increases the likelihood of conflict. A one standard deviation larger decrease in water mass more than doubles the likelihood of local conflict, which is a substantial effect. We find considerable heterogeneity in the effects by water supply factors. Acting as a buffer, access to groundwater reduces the effect of water mass change on conflict. We find no robust evidence for differential effects by water demand factors on conflict. Yet, our results show that a higher water demand amplifies the negative effects of droughts on local water mass. Moreover, the results indicate that studies focusing on the effects of contemporaneous droughts tend to underestimate the scope of their effects as local water availability responds strongly not only to current but also to past droughts.

Our results highlight that governments' water resource management strategies play a crucial role not only for climate change adaptation but also for reducing the local potential of social conflict. Facilitating access to groundwater can reduce the susceptibility to variations in rainfall, also reducing the occurrence of localized social conflict.

Chapter 5

Discrimination and inter-group contact in post-conflict settings: Experimental evidence from Colombia

Joint work with Marcela Ibañez Diaz and Lina Maria Restrepo Plaza

5.1 Abstract

After a civil war, community support for the reintegration of ex-combatants is crucial for peace-building. Using a crowdfunding campaign to promote business ideas of trainees at a vocational school (SENA), we study the process of peace-building in Colombia. We investigate whether university students discriminate against ex-rebels and test if mediated inter-group contact generates positive attitudes towards them. Our results show that compared with other trainees, there is no discrimination against demobilized ex-guerrillas in terms of donations, but there is a substantial degree of prejudice and skepticism towards them. Mediated inter-group contact improves attitudes towards the demobilized. Hence, the use of media could be a suitable instrument to sensitize people in post-conflict settings to support the peace-building process and boost positive attitudes towards ex-rebels.

5.2 Introduction

A peace declaration and the disarmament of fighters are the first steps in reconstructing peace after a civil war. In order to sustain the declared peace, a successful social and economic reintegration of ex-fighters is necessary as post-conflict societies risk recidivism once ex-combatants feel socially isolated and become economically worse off (Collier and Hoeffler, 2004; Knight and Özerdem, 2004). Yet, the success of the reintegration process depends crucially on the attitudes and behaviors of a society towards its ex-combatants (Bauer et al., 2017; Kaplan and Nussio, 2018). If community support for reintegration is either missing directly, through discrimination in personal encounters with ex-combatants, or indirectly, through a lack of societal support, the peace reconstruction efforts of policymakers may fail.

Community support for the reintegration of ex-combatants is a crucial but also challenging point. On the one hand, the community has an incentive to overcome violence; on the other hand, the civil society has suffered under the violent acts of former combatants (e.g. Miguel and Roland, 2011; Minoiu and Shemyakina, 2014; Bertoni et al., 2019), causing fear, mistrust and skepticism towards fighters. Moreover, civil wars segregate and polarize a society, causing division among citizens along diverse dimensions like "enemy vs. friend" or "offender vs. victim" (Cilliers et al., 2016). These in-group/out-group stereotypes - once established – often persist even when conflict ends and may be manifested in discriminatory behavior.

In this paper we study the process of disarmament, demobilization, and reintegration (DDR) after the peace agreement between the Colombian government and the Revolutionary Armed Forces of Colombia (FARC–EP) in 2016. Colombia is a suitable setting for our research as peace construction is at the forefront of the political agenda. However, a large fraction of the population (50.2%) rejected the peace referendum in 2016, showing that polarization and scepticism in the society is high, and raising the question of what is driving the rejection of peace.

This paper addresses the relevance of discrimination against demobilized persons in the peace-building process in Colombia. The objective of the paper is twofold. First, by measuring attitudes and behaviors of university students towards former combatants, we assess to what extent discrimination and prejudices are present towards demobilized ex-guerrillas, and whether this discrimination is based on a dislike of demobilized persons ('taste base discrimination (Becker, 1971)) or rather on subtle automatic discriminatory behavior ('implicit discrimination' (Bertrand and Mullainathan, 2005)). Second, we test a potential mechanism used to both sensitize a civil society towards the peace process, and support acceptance towards reintegrating ex-guerrillas by employing the contact hypothesis as first defined by Allport (1954). Successful social reconstruction requires a change in attitudes towards former fighters, rebuilding trust and removing threats to collective identities so that former conflicting groups can live and work together peacefully and accept each other (Nadler, 2012).

Given the doubts and skepticism in the society, it is relevant to understand what the most effective mechanisms are to promote support for the peace process. We focus on the population group of university students as they are a sizeable and growing group that represents the potential employers, and policy makers in the future.[1]

To analyze the behavior and attitude of the civil population towards reintegration, we run a crowdfunding campaign with more than a thousand participants in four private and public universities in Colombia. Participants are invited to contribute part of their earnings in a real effort task to support the business ideas of vocational trainees enrolled at the National Training program (SENA). This institution has provided technical and technological training for over 50 years. The crowdfunding campaign is suitable setting to investigate reintegration, as it comprises two critical dimensions: the integration of ex-combatants into the labor market as well as social acceptance of different population groups.

Our experimental design exogenously varies the information that participants receive about the beneficiary's group identity. This manipulation allows us to determine whether participants show less support for the business ideas of demobilized trainees than to the business ideas of their non-demobilized counterparts. In a between-subject design, we also vary the information available to participants on the socio-economic characteristics of the beneficiaries, which allows us to capture two different forms of discrimination: 'total' and 'taste-based'.

Following the literature on mediated contact (e.g. Voci and Hewstone, 2003; Turner et al., 2010), we test whether positive attitudes towards demobilized persons can be generated through contact with ex-guerrillas via a video. Half of the participants were randomly exposed to a 5-minute video in which two trainees presented themselves and their business ideas; in one video the trainees were demobilized and in the other they were non-demobilized. By comparing differences in support in the crowdfunding campaign given to non-demobilized and demobilized beneficiaries in the contact treatments with those in the no-contact treatments, we evaluate the effectiveness of the contact to decrease discrimination.

We decided to use a low-intensity, indirect, and temporarily brief contact situation, via media, as a proxy for mass communication, which is a cost effective way to address the general population. In addition, the video enables us to ensure that the contact is overall positive and comparable. Due to the short contact duration, our estimates can be regarded as a lower bound and a first step to sensitize the population.

Apart from donations, we investigate whether there is prejudice towards demobilized ex-rebels, by asking participants about their attitudes towards demobilized ex-rebels and the peace-building process. Using a single category implicit association test (SC-IAT) (Karpinski and Steinman, 2006) we further study 'implicit discrimination',

[1]Gross enrollment rate in tertiary education amount to 55% in Colombia and is on a positive trend (Worldbank, 2020).

which refers to subtle automatic discriminatory behavior (Bertrand and Mullainathan, 2005).

This paper contributes to the growing literature on peacebuilding. While most existing studies focus on the reintegration process from the perspective of ex-fighters (e.g. Annan et al., 2011; Betancourt et al., 2010; Gilligan et al., 2013; Humphreys and Weinstein, 2007), we consider the attitudes of the civil population instead. Relatively few studies investigate discrimination towards ex-combatants, and their results vary. Osborne et al. (2018) find that Ugandan community members committed 15% fewer resources to ex-combatants in a cooperation and sharing game, compared to other community members. Cardenas and Mendez (2014) support this finding, showing that in experimental games in Colombia less resources are distributed to ex-combatants compared to displaced people. On the contrary, the findings by Bauer et al. (2017) show no preference-based discrimination and mistrust towards ex-combatants in Uganda. We advance this research by assessing the diverse dimensions of discrimination towards ex-combatants undergoing reintegration, considering support, attitudes, and implicit discrimination. Furthermore, we focus on the process of changing attitudes towards ex-combatants by highlighting the fact that individuals are reintegrating, rather than focusing on their past identity as guerrillas, and by testing how mediated inter-group contact affects discrimination.

While ample empirical evidence shows that inter-group contact is a good tool to change attitudes towards stigmatized groups (see for example Pettigrew and Tropp, 2006, for an overview), evidence on the impact of inter-group contact in post-conflict settings is still limited (Al Ramiah and Hewstone, 2013). Evaluating a 4-day peace workshop with inter-group contact, Malhotra and Liyanage (2005) provide evidence that the treatment increases empathy and donations towards the conflicting group. Paluck (2009) analyzes the effects of listening to a radio soap opera involving positive contact between Hutus and Tutsis on participants' perceptions about social norms in a field experiment in Rwanda. She shows that in inter-group settings participants' perceptions and behavior change, whereas personal beliefs remain constant. Scacco and Warren (2018) support this finding. Using a field experiment in Nigeria, they conclude that positive inter-group contact decreases discriminatory behavior and increases generosity towards the conflicting out-group, but no changes are observed in stated prejudices. This paper provides evidence on the effects of indirect contact on various behavioral and attitudinal outcomes in a post-conflict society from a different cultural and geographical setting, namely from Colombia. By using a mediated contact situation in the form of a video, we provide two distinct and valuable contributions to the literature; first, we supplement the literature with a distinct form of contact that is controllable, relatively cheap in its costs, and easy to up-scale, and second, we contribute to the literature on the role of media in conflict and peace transition (Yanagizawa-Drott, 2014; Armand et al., 2020).

Our results show that there is no discriminatory behavior towards demobilized persons in the donation decisions of participants in the crowd-fund campaign. However, since charitable giving might not be sufficient in demonstrating a willingness to discriminate, we complement our analysis with attitudinal measures. We find that non-discriminatory behavior coexists with discriminatory feelings of prejudice and fear, as reported by the survey's attitudes. The mediated contact treatment increases donations for non-demobilized recipients and demobilized trainees once crucial skills are highlighted. Participants in the contact treatment report feeling more comfortable with demobilized individuals, and like them more compared to the baseline treatment. Hence, our findings indicate that increased contact decreases taste-based discrimination. We find no evidence for crowding-out effects of donations by the contact for any subgroup.

The remainder of the paper is organized as follows. Section 2 describes the geographical and historical context of the study. Section 3 presents the experimental design and procedure, while section 4 discusses the data and the empirical methodology. In section 5 the empirical results are presented. Section 6 shows some robustness checks whereas section 7 discusses important findings and concludes.

5.3 Local Context

Colombia has a long history of armed conflict. The conflict between the government, left-wing guerrilla groups, paramilitaries, and criminal syndicates began in the mid-1960s and is rooted in the civil war, called 'La Violencia' (1948-1958) (UNRIC, 2018). Starting as a political and social conflict between left-wing rebel groups and the government, it turned into a drug war with mostly economic incentives during the 1970s and 1980s. Overall, it is one of the most long-standing armed conflicts and among the most violent, with over 220,000 deaths and 6 million internally displaced people (Sánchez et al., 2013).

According to Memory History National Center (CNMH), Colombia has experienced six DDR processes. The first one started in the early 1980s when president Belisario Betancur Cuartas' government and three guerrilla groups - the Colombian Revolutionary Army (FARC), the Popular Liberation Army (EPL), and 19th of April Movement (M19) - agreed on the reintegration of over 2,000 ex-combatants. The second one led to more than 7,000 demobilized people and occurred in the late 80s and early 90s when peace agreements were reached between president Barco and the M19, and president Gaviria and the EPL plus other regional militia groupings. The third wave started in 1994 and is still ongoing. It involves over 30,000 people including all relevant guerrilla groups. The fourth wave happened between 2003 and 2006, when president Uribe negotiated the DDR process with more than 31,000 individuals connected to paramilitary groups. The fifth covered the period 2007 to 2015 (before the last Peace Accord), with 16,310 demobilized ex-combatants. The last DDR wave started in 2016 with the Peace Process signed by president Santos with the FARC when the reintegration of over 8,000 former guerrilla members was negotiated and signified the end of the Colombian irregular war.

The 2016 Peace Agreement offered the relocation of demobilized ex-combatants to transitory areas, and a 2 million COP (500 €) lump-sum transfer to facilitate their social reintegration. To reduce recidivism and poverty outbreaks, legally accredited former FARC members were entitled to 90% of a minimum salary for up to two years. Additionally, to promote economic reintegration, the parties negotiated the possibility for subjects to be granted access to 8 million COP (2000 € of seed capital for proven productive projects). Finally, demobilized persons were given priority for formal education, knowledge homologation and housing benefits, among others. In exchange, they were required to comply with the law, provide a truthful account of their experiences, show remorse for their actions, and comply with the negotiated ceasefire (Unidadvictimas, 2017). As part of the education program, demobilized persons received vocational training courses at the National Training Service (SENA). SENA is a public institution that provides technical and technological education to youth and adults in fields like Administration, Agriculture, Architecture, Construction, Design, Electricity, Electronics, Mechanics, and Technology. By 2017, approximately 28,000 ex-combatants had received vocational training, and recently more than 2,900 FARC demobilized members enrolled in SENA (Valero, 2018). Many of the trainees want to start their own business after completing the program. One limitation, though, is the lack of access to credit sources. Based on the capital constraints that trainees face, we decided to launch a crowdfunding campaign to provide support for their business ideas.

The crowdfunding campaign took place in two major cities of Colombia: Santiago de Cali and Medellín, the second and third largest cities in Colombia, with over two million inhabitants. Both cities were strongly affected by the Colombian war and suffered from major violence during the conflict. Drug cartels operated in Medellín and Cali during the 1980s and 1990s and FARC was prominent in rural areas. The two cities are important reintegration areas, too. In total, 73,532 persons have been demobilized until November 2018 in Colombia; whereby 45,730 demobilized collectively, and 27,802 individually. Medellín and its metropolitan area has the highest concentration of reintegrating combatants, with around 5,232 persons, corresponding to 8% of the demobilized population. In Cali, 1,778 demobilized persons are registered, corresponding to 3% of the population.[2] Demobilized persons often like to live in big cities, as it allows for an anonymous life and there are more job and educational opportunities than in rural locations (Caramés et al., 2006).

[2] The numbers were given by the agency of reintegration, and normalization (ARN) in a personal request.

5.4 Experimental design and procedures

5.4.1 Experimental design

To study the existence and magnitude of discrimination and prejudices towards reintegrating ex-guerrillas, and the impact of indirect contact on attitudes towards demobilized persons, we use a three-stage experimental design. In the first stage, participants solve a real effort task in which they receive an initial endowment.[3] The task is to observe three figures and pair the figures with the same shape, while one image is a rotated version of the other. Participants receive a fixed payment of 10,000 COP (3 €) if they manage to form 10 pairs. The task is constructed such that everyone should be able to pass it, and in fact, each participant did so. After finalizing the initial task, all participants watch a 3-minute video presenting the organization SENA. In this stage, using a neutral frame, we explain that trainees at SENA are searching for funding to realize their business ideas. We ask participants if they want to support the trainees' business ideas and, if so, the amount they want to donate from their earnings. Participants can select donations between zero and 10 000 COP (3 €), in increments of 1000 COP (0.3 €). In this stage, we introduce the treatments described below.

In the second stage, we apply a single category implicit association test (SC-IAT) based on Karpinski and Steinman (2006). In this test, participants have to quickly associate the objects (figures and words) displayed in the middle of the screen with the words that appear on the top. Each participant plays two rounds, with 72 randomly chosen trials, in which the order of the rounds is randomized[4]. The rounds vary whether the word *demobilized* is written below the word *good* or the word *bad*. The idea behind this test is that persons will likely be faster in the round where the word *demobilized* is correctly paired with their mental association (*good* or *bad*). To facilitate understanding of the task, each participant plays introductory practice rounds of 24 trials. For a detailed description of the test, see the instructions of part 3 in Table C.6 in the appendix or the description of the test in Karpinski and Steinman (2006).

In the final stage, participants complete a post-experiment questionnaire. We ask participants about their perceptions of the peace process; their attitudes towards demobilized, poor and displaced individuals; their conflict experiences; general personality characteristics; and additional basic socio-economic characteristics like age, gender, and the subject of study. The final questionnaire, as well as the experiment instructions, can be seen in the appendix in Table C.6.

[3] The test is publicly available in the experimental library of psytoolkit.org constructed by Stoet (2017).

[4] The pool of objects consisted out of 10 positive and 10 negative associated words and 10 images associated with demobilized persons

5.4.2 Treatments

We implement a 2x2x2 between-subject design, where the treatments vary the information that participants receive about the SENA trainees at the end of the first stage. We manipulate three dimensions: a) the identity of the recipients (demobilized or non-demobilized), b) the information about the socio-economic characteristics of the recipients (SES or non-SES), and c) the indirect contact with persons with similar identities as the recipients (contact or non-contact). Table 5.1 presents the experimental design and number of observations per treatment.

TABLE 5.1: Treatments

		NON-SES		SES	
		Treatment	No. of obs.	Treatment	No. of obs.
No contact	Non-demobilized	T1	132	T2	133
No contact	Demobilized	T3	139	T4	127
Contact	Non-demobilized	T5	137	T6	132
Contact	Demobilized	T7	136	T8	122

To introduce the identity of the recipients, we provide a short paragraph describing the recipients on the screen. In the non-demobilized condition, we ask participants if they want to support “persons that have been completing a one-year technical training program in the National Training Service.” In the demobilized setting, we ask whether they want to support “demobilized persons that have been completing a one-year technical training program in the National Training Service.” As the beneficiaries of the program include a large population pool, the first condition helps as a control for non-demobilized population. We use the term "demobilized" as opposed to "ex-guerrilla fighters" to focus the attention on peace-building and avoid inducing negative views related to the civil war. Non-demobilized SENA trainees are an adequate control group as they are similar in socio-economic backgrounds to demobilized trainees, share a current activity, and have a comparable interest in forming their own business. The difference in donation between the non-demobilized and demobilized groups captures total discrimination.

In order to disentangle the role of perception of different abilities among the beneficiary groups from discrimination, half of the participants receive supplementary information on the socio-economic characteristics of the recipients. Participants in the information treatment, which we also refer to as SES-treatment, are informed about the general socio-economic characteristics of the beneficiaries. Hence, they read, “The beneficiaries of the funding are between 45 and 60 years old, parents, have a technical degree and few years of working experience.” If discrimination is due to perceived differences in the ability of the demobilized persons, as measured by observable characteristics such as education and working experience, this manipulation will reduce that effect. Hence, differences in donation under this treatment would reflect taste-based discrimination.

In the contact treatment, which is our third manipulation, we expose participants to a 5-minute video with two personal stories about the respective SENA trainees.[5] In the video, two trainees – a woman and a man - present themselves and their business ideas. The experimental condition varies whether the videos correspond to personal stories of demobilized or non-demobilized trainees. The four SENA trainees - two demobilized and two non-demobilized - recruited for the videos are comparable in terms of general socio-economic characteristics like age, place of residence and educational attainment, as well as in their business ideas. All four persons have completed a one-year course in "sustainable living" or "environmental studies" in the SENA in Cali. We conducted semi-structured interviews with them, which we used as material for the videos.[6] The variation in the identity of the trainees in the videos allows us to measure how increased contact with demobilized individuals changes social attitudes towards them, and also how it changes the distinct forms of discrimination.

5.4.3 Experimental procedures

We conducted the lab-in-the-field experiment between August and September of 2018. Our experiments took place in the laboratories of four universities: two public (Universidad del Valle in Cali and Universidad Nacional de Colombia in Medellín) and two private ones (Universidad Javeriana in Cali and Universidad EAFIT in Medellín). In total, we ran 42 sessions.

Participants in the study were university students. To increase heterogeneity in the sample and capture variation in attitudes towards conflict, we invited students from different areas of study and of different political orientation. Traditionally, public universities are known for having more politically left-oriented students compared to private universities. The students were recruited by a general announcement sent via e-mail to all university students.[7] Participants who responded to the announcement received an e-mail with the dates of the sessions and a registration link. Once registered for a session, they received a confirmation e-mail, as well as a reminder the day before the experiment. Participants received a participation fee of 5,000 COP (approximately 1.40 €) in addition to the gains from the real effort task, minus the

[5]The coordinator in the SENA in Cali provided us with a list of eight trainees that fulfilled the following criteria. a) Were taking a course in the SENA, b) have been developing a business idea, and c) were willing to take part in the crowdfunding campaign. We interviewed them and produced a small test video. We selected the four persons based on the interviews, the comparability in business ideas, and socio-economic characteristics.

[6]The interview guideline is shown in Figure C.7.

[7]Additional promotion activities like spreading leaflets and hanging posters on the campus have been used to raise the attention of students in Cali, where the recruitment was harder and show-up rates lower.

donations. Average earnings were 12,614 COP (3.60 €), or approximately 124% of a students' hourly wage.

5.5 Hypotheses

Previous experimental evidence has shown that individuals discriminate against ex-combatants (Cardenas and Mendez, 2014). Nevertheless, subjects' proclivity to discriminatory behavior might be sensitive to their characteristics. Victims are likely to have stronger negative attitudes towards ex-combatants, as they may associate them with violence and adverse effects. Alternately, persons with a left-leaning political orientation and persons from lower socio-economic backgrounds may potentially be in favor of the ex-combatants' former work and their ideology (Åse and Wendt, 2018). Hence, we expect:

Hypothesis 1: Participants will discriminate against demobilized trainees. The degree of discrimination will increase with negative experiences had during the civil war, and will be lower in public universities than private universities. Furthermore, we expect that discrimination is higher among politically right-oriented participants compared to left-oriented counterparts.

We anticipate that participants will face considerable uncertainty about the abilities of the demobilized. On the one hand, they might perceive affiliation to an armed group as a sign of discipline and conviction. On the other hand, many ex-combatants spent a significant proportion of their lives fighting and may lack education. Thus, participants may regard them as less prepared to start a business compared to the control group.

Hypothesis 2: Discrimination decreases when participants receive information on the socio-economic characteristics of the beneficiaries. However, this information is not sufficient to eliminate discrimination.

Ample empirical evidence shows that positive inter-group contact improves inter-group relations (Pettigrew and Tropp, 2006). However, a growing literature on harmful inter-group contact contrasts the positive findings (Paolini et al., 2010, 2014). Contact may humanize demobilized individuals and increase empathy, but it can also exacerbate the subjects' negative beliefs by activating their self-confirmatory bias. Since our videos display mainly positive messages regarding the potential recipients, we expect this treatment to improve attitudes and to reduce taste-based discrimination.

Hypothesis 3: Indirect contact with beneficiaries will increase donations towards business ideas and will help to reduce taste-based discrimination. Indirect contact between participants and demobilized individuals will generate more positive attitudes toward demobilized.

5.6 Data and empirical strategy

5.6.1 Measurement

In the analysis, there are two primary outcomes of interest: discrimination towards demobilized persons and the potential mechanisms to reduce it. We use various measures to capture different forms of discrimination. First, we utilize the differences in donations between the treatment groups donating to demobilized persons and those who donate to the control group to measure behavioral discrimination. We use both the percentage of persons that donated as well as the amount donated. The control and the demobilized group are quite similar in their characteristics. They only differ in the fact that the demobilized persons were ex-fighters and are now going through the governmental DDR program. Therefore, we argue that the difference in donations is a good measure of discrimination towards ex-combatants due to combat. We refer to the difference in donations in the non-SES treatments as "total discrimination".

The comparison of the differences in donation between demobilized and non-demobilized persons over the SES treatments allows us to separate different forms of discrimination. In the SES-treatment, we provide additional information on beneficiaries' educational attainment and working experience; hence, perceptions of the recipients' abilities are expected to be the same. A difference in donations between these treatments reflects a preference of one group over another based on personal preferences and taste, rather than ability. Hence, it measures "taste-based" discrimination.

Next, we compare the judgments and stated attitudes towards demobilized individuals and other identities as declared in the final questionnaire, to draw inferences on prejudices and differences in attitudes. We ask the participants to evaluate the intellectual abilities, trustworthiness, overall working motivation, hostility, and neediness of demobilized, displaced, and poor persons. Moreover, we ask them about their preferences towards these groups. Each participant uses a 5 point Likert scale to rate how much they like the respective group, how comfortable (s)he would feel meeting a group member, and how likely it is that (s)he would become friends with a member of the respective group. Out of these three items, we construct a "liking index" as a general measure of a positive attitude towards the group. The liking index gives the relative liking of demobilized compared to poor persons.

Finally, our third measure illustrates the subjects' implicit discrimination through the single-category implicit association test (SC-IAT) result. The test is a modification of the well-known IAT test for non-binary categorical characteristics. As it measures the strength of automatic mental associations using reaction times, it is hard to manipulate and avoids social-desirability responses (Fazio and Olson, 2003). We follow the improved scoring algorithm procedure first proposed by Greenwald et al. (2003) to construct the D-score. The D-score gives the average difference response latency between the two rounds divided by the "inclusive" standard deviation of subjects' response latencies. It generally has a range of -2 to 2, whereby a positive value indicates a positive attitude towards demobilized persons, and negative values represent a negative attitude.

For the subgroup analysis, we classify participants' political orientation on a 7 point Likert scale ranging from "very left-wing" to "very right-wing"; values below 3 indicate left-leaning, values above 5 indicate right-leaning, and values of 3 and 4 represent center political leanings. Additionally, we group participants based on their degree of past victimization and whether they attend a private or public university. We measure victimization with the response to the questions "Have you been victimized in the following sense: Displacement, Torture/fighting, and kidnapping.". Participants are classified as "not victimized" if they answer "no" to all three questions; "victimized" if they answer "yes" to at least one question, and "strongly victimized" if they answered "yes" to more than one question.

5.6.2 Empirical strategy

In order to evaluate the degree of discrimination towards ex-combatants and disentangle the effect of individuals' perceptions towards differing abilities among the beneficiaries, we estimate the following regression:

$$Y_{is} = \beta_0 + \beta_1 Demob_{is} + \beta_2 SES_{is} + \beta_3 Demob_{is} \times SES_{is} + \mathbf{X}'_{is}\theta + \gamma_s + \epsilon_{is} \tag{5.1}$$

where Y_{is} is the outcome of interest; either donation (donation probability and the donation amount), implicit discrimination, or the "liking index" of individual i that participated in session s. $Demob_{is}$ is a dummy variable for treatment, indicating the possibility to donate to demobilized persons, and SES_{is} is a treatment dummy showing that additional socio-economic information of the recipient was provided. The regression includes a vector X_{is} of essential socio-demographic characteristics (age, gender, major, social status, victimization, and political preferences), and standard personal characteristics (pro-sociability and religiousness) that, according to the literature, might influence donation decisions. Study subjects are included as fixed effects in the model. Session fixed effects γ_s are used to account for environmental effects. ϵ_{is} represents the individual error term. A detailed description of how we construct these measures is available in Table C.5.

To understand the impact of the mediated contact situation, a comparison between the treatments is made in the following difference-in-difference model:

$$\begin{aligned} Y_{is} = \; & \beta_0 + \beta_1 Demob_{is} + \beta_2 SES_{is} + \beta_3 Demob_{is} \times SES_{is} + \beta_4 Contact_{is} \\ & + \beta_5 Contact_{is} \times SES_{is} + \beta_6 Contact_{is} \times Demob_{is} \\ & + \beta_7 Contact_{is} \times Demob_{is} \times SES_{is} + \theta \mathbf{X}_{is} + \gamma_s + \epsilon_{is} \end{aligned} \tag{5.2}$$

where $Contact_{is}$ refers to the treatments containing an additional video in which the two beneficiaries present themselves. In the analysis, we present the estimated total effects by treatment group. β_4 is the total effect of contact for non-demobilized individuals when no information on socio-economic characteristics is provided, while $\beta_4 + \beta_5$ is the effect for this group when information on SES is provided. The effect of contact for demobilized individuals are $\beta_4 + \beta_6$ and $\beta_4 + \beta_5 + \beta_6 + \beta_7$, when no information or information on SES is provided, respectively.

Finally, we explore the heterogeneous effects of discrimination and the impact of contact. To investigate whether discrimination in charitable behavior occurs among particular social groups, we pool data from both SES and non-SES treatments and estimate the following model.

$$\begin{aligned} Y_{is} = \; & \beta_1 Demob_{is} + \beta_k Z_{is} + \theta_k Z_{is} \times Demob_{is} + \delta_1 Contact_{is} + \delta_k Contact_{is} \times Z_{is} \\ & + \eta_1 Contact_{is} \times Demob_{is} + \eta_k Contact_{is} \times Z_{is is} + \theta \mathbf{X}_{is} + \gamma_s + \epsilon_{is} \end{aligned} \tag{5.3}$$

where, Z_{is} is a vector of categorical variables indicating socio-economic characteristics that could be relevant to explain discrimination. We consider three types of group dimensions: a) past experiences of violence (no victimization, victimization, high victimization) b) type of university (public or private) c) and political orientation (left, center, right). The heterogeneous degree of discrimination when there is no contact is estimated as β_1 for the reference group and $\beta_1 + \beta_k$ for the subgroup k. In addition, we are interested in evaluating whether contact changes discrimination for each subgroup. Therefore, we estimate the impact of contact as $\delta_1 + \eta_1$ for the reference group and $\delta_1 + \eta_1 + \delta_k + \eta_k$ for each subgroup.

5.7 Results

5.7.1 Descriptive statistics

We recruited 1,070 students (244 participants in the University EAFIT, 247 in the University Nacional, 266 in the University Javeriana, and 301 in the University del Valle), and excluded 12 participants whom we identified as not observing the video, as they failed the understanding test. The distribution of subjects among treatments is mainly balanced, except for the social status variable, which exhibits some statistical yet inexplicable differences among treatments (see Table C.1 in the appendix). Ages range between 16 and 42 years old, 605 participants are males and 453 are females, and they belong to a diverse set of college majors, the most prominent beeing engineering, economics, and business administration. Table 5.2 presents the descriptive statistics of the socio-economic characteristics of the participants and Table C.5 shows a detailed description of each variable.

We ask participants about their political orientation, as well as other questions related to their past victimization and pro-sociability. Our participants report on average a 3.14 political orientation value (over 7), indicating a general left-center leaning

TABLE 5.2: Summary statistics

Variable	Mean	Median	St. dev.	Min.	Max.	N
Panel A: Socio-economic characteristics						
Age	20.85	20.00	3.10	16	42	1058
Female	0.43	0.00	0.50	0	1	1058
Social status	3.18	3.00	1.26	1	6	1058
Religious	4.40	4.00	2.11	1	7	1058
Political preference	3.14	3.00	1.20	1	7	1058
Prosocial	0.53	0.52	0.13	0	1	1058
Panel B: Outcome variables						
Donation (Dummy)	0.57	1.00	0.50	0	1	1058
Donation amount	2.39	1.00	3.05	0	10	1058
IAT-test (D-score)	0.05	0.03	0.38	-1.32	1.51	1057
Liking index	-0.39	-0.33	0.55	-4	1.67	1058

Note: The table reports descriptive statistics of survey and experimental measures. A detailed description of the measures is in Table C.5.

orientation. The victimization index ranging from 0 to 1, and measures exposure to violence in terms of forced displacement, sexual assaults, direct attacks, and loss of relatives due to violence. We find the average victimization score to be 0.084, and find no significant differences among treatment groups. Finally, the mean prosociability index, comprising altruistic, fair, and normative behavior, is 0.53, implying our participants to have a good sense of other-regarding preferences. Again, no statistical differences appear among treatments.

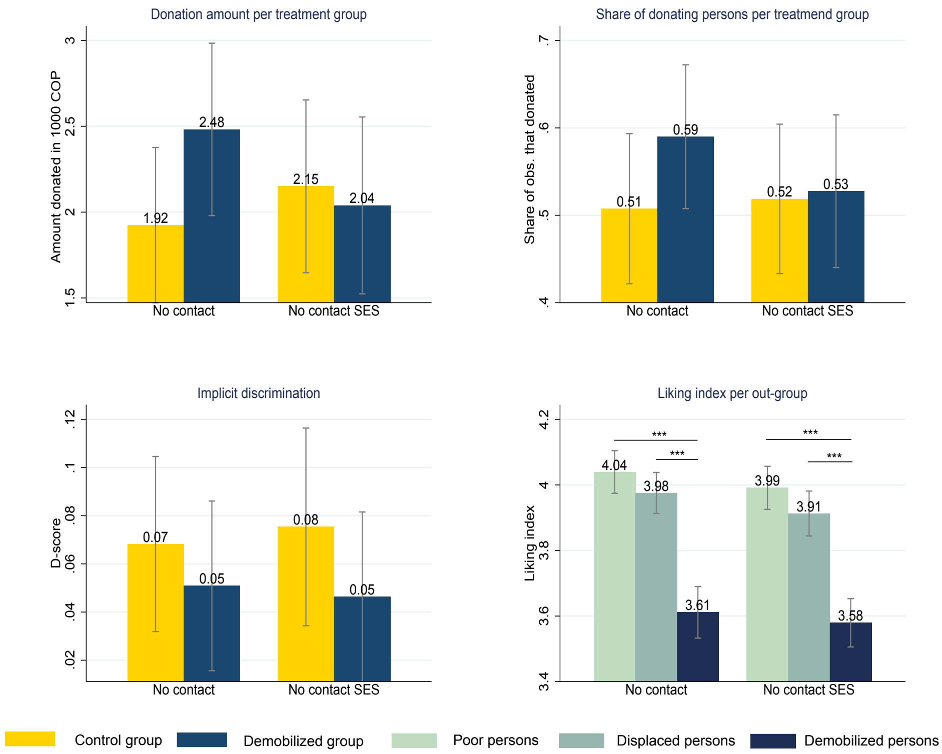
In the total sample, 56.9% of participants donated, and the average donation is 2,386.58 COP out of a possible donation of 10,000 COP, reflecting similar behavior as is observed in standard dictator games. 30% of those who donated gave less than half the endowment, 16% donated precisely half of it, and 8.5% donated all. In general, donations were more generous in private universities than in public universities (38% higher, p-value=0.0000) and in Medellín than in Cali (29% higher, p-value=0.0004). There were no significant differences observed between genders.

5.7.2 Discrimination

Donations

The average value of the donations and the proportion of participants who sent a donation in each non-contact treatment are presented in the upper graphs of Figure 5.1. We find that about half of the participants supported the crowdfunding campaign. In the baseline treatment (T1), 51 percent of the participants made a donation. The average donation represents 19 percent of the endowment. In the treatment where participants could donate to support a demobilized person (T3), 59 percent of the participants donated, and the average donation was about 25 percent of the endowment.

FIGURE 5.1: Discrimination in distinct dimensions



Note: The figure reports differences in donation and perceptions with respect to (non-)demobilized persons and the corresponding confidence intervals of 95%. In total, 531 observations are in these treatments.

Defining total discrimination as the difference in average donations to SENA trainees (1.92) and demobilized SENA trainees (2.48) in the non-SES treatment, we find that there is no total discrimination. The Wilcoxon rank-sum test shows no statistically significant difference at the 10% level in the distribution of the value donated to both groups. We also find no significant difference in the likelihood to donate to both groups (Person Chi-squared p-value=0.173 and Fisher exact test p-value=0.107).

Taste-based discrimination will occur if participants donate less to demobilized SENA trainees than other SENA trainees, given that the beneficiaries are comparable in terms of education and experience. We find that in SES treatments, where participants receive additional information on the characteristic of the beneficiaries, the value donated is not statistically different (2.15 vs. 2.04) between demobilized and other SENA trainees (Wilcoxon rank-sum test p-value=0.8525), nor is the likelihood to receive a donation (Person Chi-squared p-value=0.888 and Fisher exact test p-value=0.493). Hence, our results show no taste-based discrimination towards demobilized persons.

Charitable giving not only depends on the characteristics of the beneficiaries, but is also influenced by socio-economic and personality characteristics of the donor (Bekkers and Wiepking, 2011). To improve the precision of our results and to account for differences in the distribution of socio-economic status between treatment groups, we additionally estimate the model in Equation 5.1 that includes basic socio-economic and personality factors as well as session fixed effects. The estimates reported in Table 5.3 are in line with the descriptive results. We find no significant differences in the likelihood to donate (column 1) to demobilized compared with non-demobilized trainees. If anything, demobilized beneficiaries received a higher value in donations than the control treatment (column 2).

TABLE 5.3: Charitable behavior and attitudes towards demobilized persons by treatment

	(1)	(2)	(3)	(4)
	Donation	**Donation amount**	**Liking index**	**IAT-test**
SES	0.019	0.392	0.026	-0.000
	(0.070)	(0.345)	(0.070)	(0.049)
Demobilized	0.098	0.592*	0.038	-0.009
	(0.065)	(0.337)	(0.081)	(0.042)
SES X Demobilized	-0.054	-0.602	-0.016	-0.003
	(0.075)	(0.467)	(0.116)	(0.075)
Total effect: Demobilized with SES	0.043	0.009	-0.021	-0.012
	(0.053)	(0.360)	(0.061)	(0.055)
Control Group				
Mean Control	0.492***	1.810***	-0.448***	0.065*
Std. Dev.	(0.046)	(0.204)	(0.045)	(0.026)
Controls				
Socio-economics	Yes	Yes	Yes	Yes
Political Orientation	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Victimization	Yes	Yes	Yes	Yes
Observations	531	531	531	530
R-squared	0.199	0.234	0.171	0.148

Note: The table reports estimation results from regressing the outcome variables on the 4 treatment dummies as well as its interaction terms. The regression includes controls as shown in Table C.2. All models include session and study subject fixed effects. Clustered standard errors at the session level are in parenthesis, ***,**,* denote significance at 1, 5 and 10 percent level respectively.

In summary, we conclude that, on average, there is no discrimination against demobilized SENA trainees. These findings show that, on average, university students are as likely to support non-demobilized as demobilized SENA trainees. These results are surprising. With respect to the referendum results, we expected our participants to donate significantly less to ex-combatants. However, we know that giving in this set-up does not necessarily refer to altruism, but it comprises subjects' norms about sharing (Camerer, 2011). Thus, it could be that our participants do not feel comfortable directly discriminating against the demobilized, even if they implicitly dislike them. Unfortunately, we have not elicited normative or empirical expectations. Nonetheless, if subjects are secretly discriminating ex-combatants, we shall see some differences in the implicit association test or the attitudes towards them. In the next section, we provide some complementary evidence in that direction.

Implicit association test

The implicit association test (IAT) captures automatic associations towards the demobilized population. Figure C.1 in the appendix presents the distribution of the IAT (D-score) test results overall treatments, and the bottom left graph in Figure 5.1 reports the average score in the no-contact treatments. If participants, in general, hold subtle negative attitudes towards demobilized individuals, the IAT (D-score) will be negative. Referring to Figure C.1, the test results follow a normal distribution. In the treatments with no contact, the index is, on average, 0.06 with a 95% confidence interval between 0.028 and 0.092. A student's two sided t-test indicates that the mean value is significantly larger than zero (p-value=0.001). This indicates that, on average, participants hold a neutral to positive attitude towards demobilized persons.

Assignment to treatments is not expected to change implicit associations towards the demobilized group. Yet we test this by estimating Equation 5.1 with D-score as the dependent variable, and present the results in column 4 of Table 5.3. The regression results confirm that there are no significant differences in associations between participants in T1 and T3.

Attitudes towards demobilized

An alternative measure of discrimination is to consider differences in reported attitudes towards demobilized persons compared with other population groups with similar socio-economic characteristics. To measure attitudes, we built a "liking index" for different population groups, consisting of the average value of the response to three items measured on a 5 point Likert scale: a) 'willingness to become friends', b) 'comfortableness in meeting group members' and c) 'general sympathy towards the group.' The bottom right graph in Figure 5.1 presents the average rating, on a 5-point Likert scale, of demobilized individuals, poor people, and displaced persons' aggregate liking index in the baseline treatments. A detailed picture of the single items and further dimensions is shown in Figure C.2 in the appendix. We find that participants state that they like demobilized persons less compared with the other two population groups (poor or demobilized people). The composite index is significantly lower for demobilized persons than for displaced or poor persons (Wilcoxon sign-rank test p-value < 0.01).

To investigate how our treatments change attitudes towards demobilized, we regress the difference in the liking of demobilized compared with the liking of poor people on treatment variables according to Equation 5.1. The regression result, which is presented in column 3 in Table 5.3, shows that, on average, demobilized persons are rated 0.44 points lower than poor persons are, which corresponds to around 63%

of a standard deviation. This difference is significant at the 1% level. It is constant across treatment groups and is robust to corrections for multiple hypothesis testing. Participants report being significantly less willing to become friends with demobilized persons than other population groups (Wilcoxon sign-rank test p-value<0.01). They also report feeling less comfortable meeting with demobilized persons (Wilcoxon sign-rank test p-value<0.01), and perceive them to be less sympathetic and less trustworthy than other population groups (Wilcoxon sign-rank test p-value<0.01).

Regarding the degree of discrimination towards ex-guerrillas, we conclude that the results partly support Hypothesis 1. In the no-contact treatments, the likelihood of receiving a donation nor the value of the donation received are lower for ex-combatants compared to other trainees at the 5% significance level. Yet, we find a small but significant positive discrimination in the SC-IAT test, in contrast to a large and significant negative attitude towards the demobilized population compared with poor people. Why is it that negative feelings towards ex-combatants are not translated into lower donations? One potential explanation is that despite the scars of war, participants are hopeful that peace-building will work, and they understand the importance of supporting it.

5.7.3 The effect of contact on discrimination

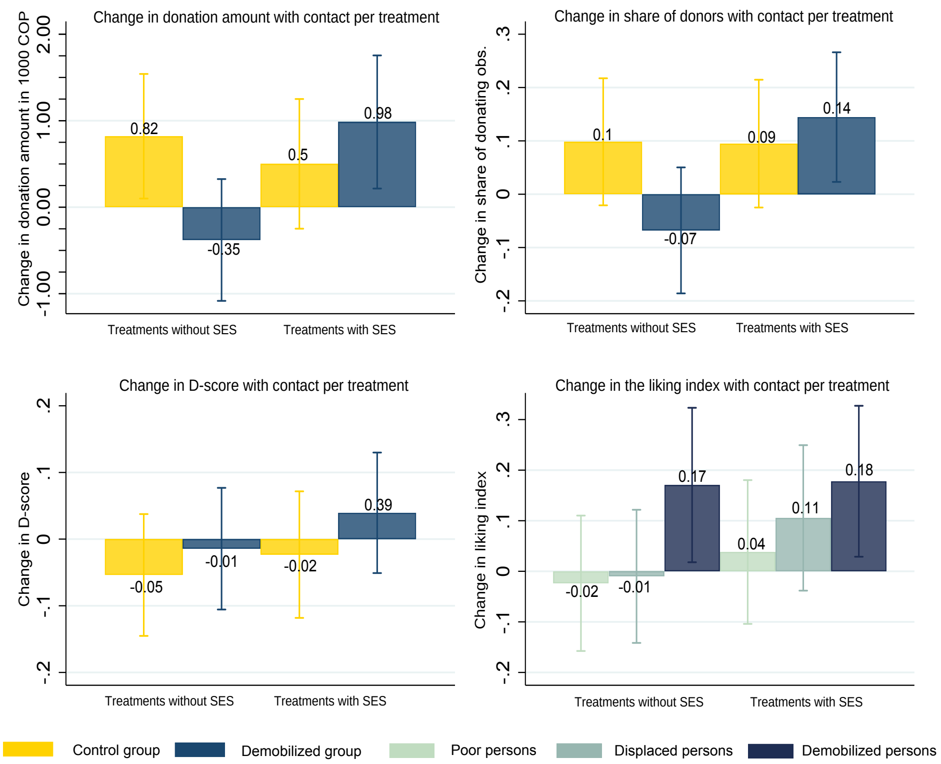
Donations

We expected that indirect contact with the beneficiaries, in the form of a video, would increase donations. Confirming this hypothesis, we find that in treatments with contact, participants are 12% more likely to donate and donate 21% more money than in the no-contact treatments. This difference is statistically significant at the 5% level (Student's t-test p-value=0.0334 and 0.0128).

More interesting questions, however, are whether the videos of demobilized persons and other trainees have the same impact, and if the videos induce more positive attitudes towards demobilized as suggested by the contact theory. Figure 5.2 presents the differences in the outcome variables between no-contact and contact by treatment. The upper graphs show the effect on the donation amount (left panel) and the share of persons donating (right panel). Descriptively, we find that the non-demobilized contact has mainly an effect on the donation amount. Donations to non-demobilized persons increase by 820 COP in the non-SES treatment (Student's t-test p-value=0.0257), whereas the likelihood to donate does not increase significantly.

The inter-group contact theory states that one important channel to reduce prejudices is through an increase in empathy. Therefore, we hypothesized that the contact treatment would especially help to reduce taste-based discrimination. Our results confirm hypothesis 3. The proportion of donating participants increases by 14% in the SES treatment supporting demobilized persons (Student's t-test p-value=0.0199) and the value of the average donation to the demobilized raises by 980 COP (Student's

FIGURE 5.2: Change in discrimination by contact in distinct dimensions



Note: The figure reports the differences in the donation, the IAT-test score and in perceptions with respect to (non-)demobilized persons by contact and the corresponding confidence intervals of 95%. In total, 1058 observations are in these treatments.

t-test p-value=0.0123). No significant changes are found for the non-demobilized group.

To test for the robustness of the previous results, we estimate Equation 5.2 and report the estimated total effects on the likelihood to donate by subgroup in column 1 of Table 5.4. We find that contact has a positive effect on the donations to non-demobilized trainees. The likelihood to donate to non-demobilized beneficiaries increases significantly, by 11.9%, when participants receive information on SES. In the non-SES treatment, the magnitude is comparable yet insignificant. Contact also increases the likelihood that demobilized participants receive a donation, but only when participants receive information on their abilities. In the treatment with contact and SES, demobilized beneficiaries are 13.1% more likely to receive a donation compared to demobilized recipients in the SES treatment without contact. Contact has a very similar effect at the intensive margin. Column 2 in Table 5.4 presents the total effects of contact on the average value of the donation. The value donated to non-demobilized increases by 879 COP compared to the no-contact treatment. Whereas donations to demobilized increases by 928 COP when participants receive information on SES, in the condition with no information on SES, contact has no significant effect on the value donated to demobilized participants. Once corrected for the family-wise error rate using the Sidak procedure, the effects on the likelihood

TABLE 5.4: Evaluation of contact

	(1) Donation	(2) Donation amount	(3) Liking index	(4) IAT-test
Control	0.111	0.879**	0.009	-0.035
	(0.078)	(0.361)	(0.062)	(0.046)
Control + SES	0.119*	0.613	-0.043	-0.019
	(0.060)	(0.405)	(0.048)	(0.045)
Demobilized	-0.074	-0.307	0.159**	-0.029
	(0.060)	(0.350)	(0.063)	(0.058)
Demobilized + SES	0.131**	0.928**	0.124*	0.036
	(0.059)	(0.361)	(0.069)	(0.047)
Controls				
Socio-economics	Yes	Yes	Yes	Yes
Political Orientation	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Victimization	Yes	Yes	Yes	Yes
Observations	1058	1058	1058	1057
R-squared	0.134	0.170	0.161	0.091

Note: The table reports estimated impact of contact on outcome variables as estimated in Equation 5.2. The regression includes controls as shown in Table C.2. All models include session and study subject fixed effects. Clustered standard errors at the session level are in parenthesis, ***,**,* denote significance at 1, 5 and 10%.

to donate become insignificant. Yet, the results on the intensive margin hold.

To summarize, contact shows slight evidence for a positive effect on donations of non-demobilized beneficiaries and a strong effect on donations of demobilized beneficiaries once additional information is provided. Contact seems to decrease taste-based discrimination.

Implicit association

The bottom left graph of Figure 5.2 presents the changes in D-scores between contact and no-contact treatments for the different beneficiaries and treatments. Descriptively we find that contact does not change implicit discrimination against the demobilized in any of the treatments. To test for these results, we estimate Equation 5.2, taking D-score as a dependent variable. Column 4 in Table 5.4 presents the total effects by treatment. The results confirm that there are no significant differences across the treatments in the implicit association test. This null-effect is not surprising, as implicit associations are time-persistent and change slowly over time (Rydell and McConnell, 2006).

Attitudes

Can increased contact with demobilized individuals mitigate their poor rating on the liking index and promote personal encounters with them? The descriptive results answering these questions are presented in the bottom right graph of Figure 5.2. Figure C.2 in the appendix depicts the descriptive results for each sub-category. We find that whereas contact has no significant effect on the liking index towards poor people and displaced populations, it has a significant positive effect on the liking of demobilized participants. In the contact treatments, the liking rating of demobilized persons is 0.17 points higher compared to the no-contact treatments (Student's t-test p-value = 0.001). The increase is similar for treatment without SES (total discrimination) and with SES (taste-based discrimination). While contact has a positive effect on attitudes, it does not fully offset the difference between demobilized and poor persons. Column 3 in Table 5.4 presents the total estimated effect by treatment when we use differences in the liking index of demobilized and poor people as the dependent variable in Equation 5.2. The results indicate that when participants have contact with a demobilized individual, attitudes towards them improve significantly. The gap in the liking index of demobilized individuals compared to poor people reduces by one third after indirect contact.

With respect to the single components of the liking index (see Table C.3), we find that the positive effect of contact is mainly associated with a higher willingness to have a personal encounter with demobilized beneficiaries. The participants who watched the personal video of demobilized beneficiaries expect a higher comfortableness when meeting demobilized persons than participants in the baseline treatment (Student's t-test p-value$<$0.001). The likelihood of becoming friends with a demobilized person does not significantly change with the video, nor does the rating of how sympathetic demobilized participants are.

Thus, our results provide evidence that contact changes taste-based discrimination. Attitudes and intentional behaviors change after contact by reducing fear (indicated by a participant reporting feeling more comfortable in meeting with demobilized persons) to a more positive perception.

5.7.4 Heterogeneity in behavior

Heterogeneity in discrimination

People may perceive ex-combatants differently and act differently towards demobilized individuals depending on their conflict experiences and personal preferences. In order to investigate heterogeneity in participant behavior, we focus on three dimensions that are likely correlated with perceptions towards the demobilized: degree of victimization, socio-economic background as measured by private vs. public university attendance, and political orientation of the participant. Table 5.5 reports the degree of discrimination by each subgroup on the four relevant measures.

TABLE 5.5: Heterogeneous effects in behavior and attitudes

	Behavior and attitudes No Contact				**Impact of Contact**			
	Donation	**Donation amount**	**Liking index**	**IAT-test**	**Donation**	**Donation amount**	**Liking index**	**IAT-test**
Panel A: Victimization	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No Victimized	0.072	0.197	-0.419***	0.069***	0.011	0.272	0.167**	-0.028
	(0.047)	(0.236)	(0.022)	(0.013)	(0.050)	(0.287)	(0.057)	(0.032)
Victimized	0.051	0.592	-0.449***	0.015	0.158	1.044	0.133	0.115
	(0.114)	(0.815)	(0.045)	(0.044)	(0.097)	(0.816)	(0.094)	(0.109)
Strongly Victimized	-0.205	-0.579	-0.324**	0.028	-0.032	-0.749	-0.261	0.040
	(0.193)	(1.593)	(0.097)	(0.074)	(0.149)	(1.229)	(0.245)	(0.143)
Panel B: Type of University								
Private	0.127	0.444	-0.416***	0.060**	-0.031	-0.144	0.139	0.026
	(0.059)	(0.341)	(0.037)	(0.021)	(0.056)	(0.311)	(0.083)	(0.049)
Public	-0.030	-0.024	-0.424***	0.061	0.087	0.712	0.136**	-0.033
	(0.058)	(0.322)	(0.029)	(0.030)	(0.066)	(0.467)	(0.043)	(0.044)
Panel C: Political Orientation								
Left	0.049	-0.313	-0.392***	0.082**	0.025	1.086	0.060	0.035
	(0.076)	(0.458)	(0.038)	(0.027)	(0.063)	(0.503)	(0.090)	(0.054)
Center	0.052	0.472	-0.420***	0.050**	0.018	-0.063	0.151**	-0.023
	(0.059)	(0.315)	(0.025)	(0.018)	(0.051)	(0.326)	(0.045)	(0.046)
Right	0.255	1.062	-0.665**	-0.002	0.189	-0.171	0.663	0.010
	(0.180)	(0.712)	(0.212)	(0.096)	(0.203)	(0.728)	(0.427)	(0.174)
N	1058	1058	1058	1057	1058	1058	1058	1057

Note: The table reports the total differential effect by personal characteristics in discrimination. The regression include controls as shown in table C.2. All models include session and study subject fixed effects. Clustered standard errors at the session level are in parenthesis, ***,**,* denote significance at 1, 5 and 10% including the multiple hypothesis testing correction by Sidak.

The first four columns report the differences for each of the outcomes of interest when there is no contact, while columns 5 to 8 report the impact of contact on discrimination. Panel A reports the different effects by victimization status. Panel B reports by university type and Panel C depicts the heterogeneous effects by the political orientation of the participants. All results are adjusted for multiple hypotheses testing. We focus on total discrimination, only and do not distinguish between the SES treatment, both for simplicity and to ensure we have enough participants in each subgroup. Overall, there are only marginal differences concerning SES treatments.

Referring to the results in Panel A, we find no significant differences in charitable behavior towards demobilized beneficiaries compared to non-demobilized beneficiaries depending on a participant's experiences of violence. Neither the likelihood to donate (column 1) nor the amount donated (column 2) are significantly different for demobilized recipients compared to non-demobilized recipients for any subgroup. Surprisingly, the results show that experiences of victimization do not affect attitudes towards demobilized persons. All three groups prefer poor persons to the demobilized, and the extent of preference does not vary by subgroup. Participants with no exposure to violence have a positive and significant IAT-test, indicating some preference for demobilized individuals. This result does not hold for participants exposed to low or intense violence. However, the implicit discrimination is not statistically different across subgroups.

Neither private university students nor public university students displayed discriminatory behavior towards demobilized trainees in the crowdfunding campaign. Regarding attitudes, private and public university students report to like poor individuals more than demobilized persons to a similar extent. Similarly, they achieve equal positive implicit discrimination scores.

Concerning political orientation, the results in Panel C show no discrimination in charitable behavior by any subgroup. Nevertheless, right-oriented persons report disliking demobilized individuals relative to poor people to a more substantial degree. This finding indicates that attitudes and behaviors do not necessarily need to align with each other. Moreover, right-oriented participants have significantly lower IAT-test scores compared to the left and center-oriented participants.

We conclude that the results only partly support Hypothesis 1. We find that experiences of violence are not correlated with a higher degree of discrimination towards demobilized individuals. Private university students donate as much to demobilized trainees as to other SENA trainees and express the same degree of dislike as public university students. Right-wing participants express more negative attitudes toward demobilized.

Heterogeneous treatment effects of contact

In order to check whether sub-groups react differently to the contact treatment, we estimate Equation 5.3. Persons with negative experiences of violence or right-wing political attitudes may watch the video, focusing more on the negative aspects of the reintegration process. The indirect contact with demobilized might, therefore, strengthen their existing opinion (confirmatory bias). If this is the case, our results will show an adverse effect for prejudiced groups. Results in columns 5 and 6 in Panel A of Table 5.5 show that indirect contact with demobilized individuals does not increase nor decrease discriminatory behavior. The same is true for implicit discrimination for participants with no experience or low or high experience of victimization. Nevertheless, the results show a positive change in attitudes towards demobilized for non-victimized participants with contact.

In Panel B, we investigate the heterogeneity between public and private university students, which can be seen as an indicator of different socio-economic backgrounds, since students from wealthier households are more likely to attend a private university than students from poorer households. The indirect contact does not significantly change discriminatory behavior toward demobilized persons for any of the subgroups. We find that after watching the video, the attitudes of public university students towards the demobilized relative to poor persons are more favorable. IAT-test scores do not change with the contact.

For political preferences, we see a similar pattern. The contact does not change the difference in the likelihood to donate, the amount donated to demobilized compared to non-demobilized trainees, nor the IAT-test scores of left, center, or right-oriented participants. Center-oriented participants show more positive attitudes towards demobilized persons after they have watched the video.

We conclude that indirect contact with demobilized persons increases donations to the same extent as contact with a non-demobilized person. Non-victimized participants, public university students, and center-oriented persons show more positive attitudes towards demobilized persons relative to poor persons after the contact treatment. Hence, indirect contact has a positive effect on attitudes towards the demobilized among specific population groups. We find no adverse effects of contact on discrimination towards the demobilized. Hence, our results partly confirm Hypothesis 3.

5.8 Robustness check

We assumed that the videos of demobilized and non-demobilized trainees have a similar valence and are perceived equally. However, the persons in the videos may provoke different feelings in the participants, and the opinions towards their business idea may vary. If demobilized persons in the video are systematically perceived differently from the non-demobilized persons, our estimates will be biased. At the same time, perceptions are endogenous and can be seen as outcomes of discrimination on their own. In order to investigate whether the estimated effects of contact stem from differences in the perceptions of the video, we run further regressions controlling for these factors on the sub-sample of observations in the contact treatments. The results are shown in Table C.4 and give several insights. First, the results confirm that participants' perceptions of the persons in the video vary, and these factors influence the donation decisions. A higher perceived sympathy for the persons in the video is associated with higher support for the beneficiaries, whereas perceived hostility decreases donations and is positively associated with implicit discrimination. Moreover, support for beneficiaries is positively associated with their liking business ideas. The evaluation of their working motivation and their neediness does not affect the donation decision. Second, after controlling for these factors, the estimates of the treatment indicators are not statistically significant with respect to the donation outcomes. This means that contact has the same effect for all treatments once we control for the perceptions of the video. Hence, the different perceptions of the two videos are not driving our results.

We also test whether the distributions of liking the business ideas and the perceived sympathy are significantly different in the contact treatments and show the distributions in Figures C.3 and C.4. We find no significant differences between the distributions of the two treatments concerning liking the business ideas (Wilcoxon sign-rank test p-value = 0.2017). However, non-demobilized persons in the video are perceived as more sympathetic (Wilcoxon sign-rank test p-value < 0.01).

5.9 Discussion and Conclusion

To assess the role of community support in the peace-building process, we ran a lab-in-the-field experiment in Colombia to investigate whether Colombian students have prejudices and discriminate against reintegrating ex-guerrillas and, if so, in which dimension. Our results show that demobilized recipients are, in general, not treated differently than persons with comparable socio-economic characteristics in the campaign and, if anything, they are even slightly preferred. This finding is consistent with the idea that the affiliation to rebel groups and experiences in combat show no lasting effects, and that attitudes concerning the peace-building process change quickly. Moreover, we find no evidence for subtle negative mental associations with demobilized persons in the SC-IAT test. However, the analysis of the statements in the final survey clearly shows that the participants in our experiment are less willing to meet and become friends with demobilized persons compared to the control group. Hence, our results are in line with (Tellez, 2019), who shows that in conflict-affected regions in Colombia, persons are willing to support the peace process and grant concessions to demobilized individuals but fear for their security when it comes to personal encounters.

Two points have to be mentioned here: First of all, we measure discrimination in relation to persons with lower socio-economic backgrounds, as we think that this group is comparable to the demobilized population. Nevertheless, participants with lower socio-economic backgrounds might be perceived as having negative characteristics (i.e., lack of experience, low human capital, etc.). Thus, we cannot rule out that discrimination overall is not present in the donation decisions. However, the percentage of persons that donated and the amounts donated are in line with the findings of previous literature on charitable giving. Second, supporting a person to start her/his own business is an indirect behavior. No personal contact is necessary in the decision-making process, in contrast to most real-life job interview situations. Here our results are not clear-cut. Since we see that the participants are somewhat less comfortable meeting demobilized persons, discrimination in such a situation may be likely with respect to our results. The setting, nevertheless, is informative and relevant for several reasons. With the crowdfunding campaign, we can give evidence on two critical dimensions of reintegration, namely the reintegration into the labor market and civilian life. Since Colombia has a high share of self-employed persons, especially among those from lower socio-economic backgrounds, seeking access to credit for opening a business is a relevant situation. Moreover, indirect support can become crucial, as was the case in the peace referendum. Finally, concerning the participants in the survey, we argue that university students are an essential group, as these constitute potential future employers and customers. Future work should explore the extent of discrimination among different population groups.

Two methodological concerns arise at this point: the external validity of our results and experimental demand effects. As for the former, we know that by choosing college students, we might be setting a lower bound for our effects, and replicating the study to a non-educational sample is desirable. Nonetheless, relative to regular lab participants, ours are bringing different levels of exposure to conflict to the lab, which is a critical characteristic connecting our setting to a less controlled one. We also notice that the donation behavior in our experiment does not depart much from other lab and field dictator games, for which we believe that the incentives we provided seemed to be enough to elicit the traditional norms for charitable giving. Finally, we know that our experimental subjects could feel compelled to donate, since donating is all they can do in the experiment. If that is the case, the experimental demand effect will be present in all our conditions, and will not affect the net treatment effects.

We implemented a short-term mediated contact in our experiment to evaluate its effect on community support for reintegration. Participants in the contact treatment watched a 5-minute video, in which two recipients present themselves and their business ideas. The evaluation of contact shows that inter-group contact succeeds in increasing donations to non-demobilized and demobilized recipients. Contact increases donations to demobilized beneficiaries, but only when relevant skills are highlighted. We see that the effect mainly stems from the change in taste-based discrimination happening through a reduction in fear.

Post-conflict settings are contexts, where groups are relatively sharply segregated, tensions between the groups are relatively high as well as the emotional costs of personal encounters. Eller et al. (2012) show that in such contexts where personal contact between groups is low, indirect forms of contact affect inter-group attitudes. The critical advantage of indirect contact is its scope. Via public media, a broad audience can be reached in a short time and with low costs. Additionally, it is easier to promote positive contact and reduce the negative perceptions than in personal contact situations that are less controllable. It can be regarded as a first step in sensitizing the groups with respect to personal contact.

To answer the question, if inter-group contact is a suitable tool for peace-building, a closer look at when inter-group contact works, and for whom, is needed. Our sub-group analysis highlights that contact with demobilized individuals is likely to work better for some population groups than for others. However, we do not find a negative change of attitudes or behavior for potentially more prejudiced participants that are potentially more inclined towards negative aspects in the contact. Heavily victimized persons and more right-oriented participants change neither donations nor attitudes after indirect contact. In conclusion, inter-group contact, and in particular mediated inter-group contact, may be an adequate instrument for post-conflict settings. It can efficiently sensitize society for ex-combatants and increase support for the reintegration process. It is easily implementable, cost-effective, and less risky in terms of potential adverse effects. However, further research is necessary to get a clearer picture of when and for whom mediated contact works.

Chapter 6

The heterogeneous effects of conflict on education: A spatial analysis in Sub-Saharan Africa

Joint work with Krisztina Kis-Katos

6.1 Abstract

In this paper, we identify under which conditions and to what extent armed conflicts harm the long-run educational attainment of children in rural Sub-Saharan Africa. By combining 66 rounds of DHS surveys with geo-coded conflict information, our study contextualizes the findings of a series of country-specific case studies on the effects of conflict on education, and provides evidence on the mechanisms through which these effects occur. Our main identification strategy compares educational losses of youth living within the same household, while also controlling for local weather shocks and countrywide dynamics in education. The effects of conflict on education are strongly context dependent. High-intensity conflicts reduce local educational attainment, on average, although this effect becomes insignificant in strong autocracies. By contrast, education is generally unaffected by localized low-intensity conflict. Human capital loss due to conflict is most severely felt in weak states, and in response to non-state based conflicts, highlighting the importance of state capacity in mediating the educational costs of local conflicts.

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6.2 Introduction

Education is a basic human right and a crucial determinant of economic and social development. However, despite recent global development goals pushing towards universal education, around 61 million children worldwide are still unable to attend primary school (UNESCO, 2017). Strikingly, nearly half of these children live in conflict-affected countries, which raises the question about the role of conflict in deterring education (UNICEF, 2017).

The literature on the effects of conflict on education is substantial, yet the available case studies yield partly contradictory results (e.g. Akbulut-Yuksel, 2014; Arcand and Wouabe, 2009; León, 2012). They present a wide range of estimates, spanning from positive effects (0.2 years more of education per conflict year) to negative effects of 0.9 years of education lost (e.g., Akbulut-Yuksel, 2014; Arcand and Wouabe, 2009; Bertoni et al., 2019; León, 2012; Lee, 2014; La Mattina, 2018; Shemyakina, 2011). These country-specific studies focus on various types of conflicts with distinct intensities and actors within specific country contexts, and fail to generalize their results to a wider range of violent conflicts and their determinants.

This study contributes to close this gap by identifying under which conditions and to what extent conflict exposure during childhood influences the subsequent educational attainment of youth in rural areas of Sub-Saharan Africa. We consider conflict characteristics (conflict severity, as measured by the conflict's yearly death toll and the types of conflict actors), individual characteristics (age of exposure to conflict and gender) as well as country and location characteristics (political regime type, economic development, ethnic fractionalization, availability of natural resources) as important determinants of conflict effects. These conditions either follow the previous literature (e.g., León, 2012) or are closely linked to the concepts of state capacity and public goods provision – the two channels we investigate in detail in this paper. By extending the geographical scope of the analysis to a regional sample of 31 countries in Sub-Saharan Africa, our empirical study generalizes the findings of country-specific case studies on the costs of conflict in terms of lost education. Sub-Saharan Africa provides the optimal setting for such a study, being one of the most conflict-ridden regions in the world. Almost half of all armed conflicts during the past 40 years have taken place in Sub-Saharan Africa (Arcand and Wouabe, 2009). At the same time, education is still far from universal in many countries of this region.

Our empirical analysis combines data from 66 Demographic and Health Surveys (DHS) with geo-coded information on conflict events, provided by the Uppsala Conflict Data Program (UCDP) (Sundberg and Melander, 2013). We determine potential conflict exposure through an exact measure of the distance between the current survey location of the 10 to 26 year old in the DHS sample and the geo-coded location of past conflict events, calculating potential exposure to violent events that have occurred within a 50 km radius of the survey location during different age periods. We measure only potential, and not actual, conflict exposure, as the DHS does not systematically record full migration histories. In order to mitigate the issue of wrongly attributed conflict history, we only focus on rural areas of Sub-Saharan Africa, as rural areas tend to have fewer migrants and the majority of displaced people either return to their homes after conflict or move to urban areas (IDMC, 2018; Awumbila, 2017). We further assess the scope of the potential bias by repeating our analysis for a sub-sample of data with migration information.

Any analysis of the link between conflict and education faces a central endogeneity problem: Omitted factors may both explain a higher local propensity to experience violent conflict at any given point in time and a lower quality of public goods provision or higher labor market incentives to drop out of school early. We address this potential omitted variable bias by including an extensive set of fixed effects along two main dimensions. First, household (or location) fixed effects absorb the geographic and socio-economic variation in the average propensity to experience conflict. Second, by including country-specific birth cohort fixed effects, we capture yearly changes in the national economic, conflict, and political environment. In our preferred specifications, we combine these two sets of non-nested fixed effects to control for common drivers of education and conflict exposure across households as well as over time within any country. We also account for time-variant local economic shocks by controlling for the local presence of weather shocks, which contribute to explaining conflict (Miguel et al., 2004; Harari and Ferrara, 2018), but also other local economic outcomes. We additionally validate our main results by using an interaction of weather shocks with the distance to the next ethnic border as an instrumental variable for past conflict exposure. In doing so, we control for the direct effects of weather shocks and ethnic diversity on schooling, and identify the effects of conflict exposure on education through the heterogeneous effect of extreme weather events due to ethnic fractionalization.

Our results show that exposure to low-intensity conflict cannot be robustly linked to educational attainment in rural Sub-Saharan Africa. But, conflicts of more substantial severity are robustly linked to average losses in local education. One additional conflict year of high intensity (with at least 1000 casualties) reduces average education by 1.4 months. The effects of conflict concentrate among the most exposed children: Among the upper 5% of children living in the most violence prone sample locations, the average losses from high-intensity conflicts reach up to 7 months.

Conflicts are especially harmful to education when state capacity is impaired. Our results show that especially conflicts by non-state actors, which are more likely to target schools during conflict, lead to educational losses. Strongly autocratic systems are more successful at sustaining public goods provision during periods of intense violence compared to weak states and strong democracies. Education in natural resource rich locations is also strongly affected by conflict. Rebel groups may strategically capture natural resources, financing their actions and harming public goods provision even in case of a conflict of similar intensity. When we compare exposure at different age periods, we find no differences on average, confirming both the early childhood as well as fetal origin theories. With respect to gender, high-intensity conflict seems to affect boys' education somewhat more negatively than girls' education.

The remainder of the paper is organized as follows. Section 2 offers a theoretical background, section 3 describes the data, while section 4 outlines the empirical strategy. Section 5 presents the empirical results and discusses issues of identification. Section 6 shows further robustness checks, while section 7 concludes.

6.3 Violent conflicts and education

Violent conflicts affect both the supply and demand for education through a wide variety of channels.

At a basic level, conflicts can directly affect the demand for education. In armed conflicts, pupils are often fighting, fleeing, or hiding instead of attending school (Sommers, 2002). Young boys are especially simple recruitment targets for armies and rebel groups, as they are easier to manipulate than adults and rarely require to be paid for their service. The fear of landmines or other physical dangers, as well as sexual violence, on the way to school often cause school drop-outs, especially among girls (Justino, 2011). Large-scale conflicts also provoke humanitarian crises, leading to massive displacement and migration that is usually very disruptive to education (Justino, 2011). Moreover, conflict affects school outcomes indirectly by reducing the incentives to invest into education. Epidemics or economic crises caused by conflicts can also inhibit necessary investments into skills (Cunha and Heckman, 2007). Physical destruction of schools increases the costs of education, through higher transportation costs of reaching the nearest school, for instance. Violent conflicts also shape the local labor market, reducing the returns to education.

The mental and physical health of school-aged children can be affected by conflict as well. Injuries, deaths, and traumatic experiences leading to psychological distress may cause children to stay home from school, compromising their cognitive and non-cognitive development (Justino, 2011; Brück et al., 2019). Additionally, environmental shocks, both in utero and in early childhood, can affect neurological development and basic mental faculties that determine future abilities (Cunha and Heckman, 2007; Barker, 1995; Almond and Currie, 2011).[1] In this regard, conflict experiences before and immediately after birth may actually affect a child's future educational attainment in a number of ways.

From a supply standpoint, violent conflicts often destroy physical capital like school buildings and road infrastructure, reducing the state's ability to provide universal

[1] See Currie and Almond (2011) and Bharadwaj and Vogl (2016) for reviews of the related literature.

access to education. The loss of human capital through teacher absence further compromises the functioning of school systems and can lead to productivity losses in the long run (Lai and Thyne, 2007; Monteiro and Rocha, 2017). During conflicts, public funds may be redirected from education towards expenditures on the military. Beyond these direct effects on education provision, a decrease in economic development from a violent conflict can lead to reductions in the demand for public goods, diminishing their marginal returns. Moreover, it can decrease tax revenues diminishing the financial resources of the government (Besley and Persson, 2014).

Education is one of the most common state-provided public goods (Daviet et al., 2016). Thus, the supply of education depends directly on state capacity, which includes the financial resources, administrative knowledge, and military and political power to establish and maintain well-functioning institutions that provide public goods and services. Countries with lower state capacity, i.e. those with poorer incomes or less quality of governance, provide fewer public goods on average, resulting in lower levels of human capital development (Besley and Persson, 2014). Moreover, the need to redirect funds from education to military activities in times of conflict is especially high when state capacity is limited (Lai and Thyne, 2007).

Violent conflicts and state capacity have common underlying roots and influence each other (Besley and Persson, 2010, 2014). While conflicts can limit state capacity, so too can the lack of adequate state capacity enable the spread of violence. The decision of a population to rebel is partially based on a state's capacity to repress insurgencies and accommodate grievances (Hendrix, 2010). Likewise, the under-provision of basic social security decreases the opportunity costs of fighting for the local population (Collier and Hoeffler, 2004). Hence, countries with lower state capacity are more likely to face revolts and at the same time have fewer resources to counteract them. Moreover, violent conflicts influence the decision to invest in state capacity in the future, preventing the establishment of robust and well-functioning institutions. This creates a volatile system of short-term rather than long-term goals, which raises the susceptibility to external shocks. Hence, we expect state capacity to be an important moderator in the relationship between conflict and education. Education in wealthier regions may be less affected by conflicts due to lower budget constraints.

Political systems face distinct incentives to invest in state capacity development: Democratic politicians direct policies to the median voter to gain the highest share of votes in order to stay in office (Downs, 1957), resulting in a high level of public goods provision following the interests of the majority. On the contrary, autocratic regimes favor transfers that target the elite (Deacon, 2009), resulting in a lower level of public goods provision. Strong states have a robustly functioning administrative system that is less susceptible to shocks. Additionally, they have more financial resources at their disposal, which protects funds appropriated to basic services from being redirected towards military engagements. Since autocratic regimes, generally speaking, direct higher amounts of public funds to armed forces rather than public goods and services provision (Deacon, 2009), the likelihood of redirection in the face of conflict is even smaller. Hence, we would expect that educational losses caused by violent conflicts are the most pronounced among weak states, followed by strong democracies, and are the least pronounced among strong autocracies.

Revenues from sources other than taxation, like natural resources, are often more volatile as they depend on the world market demand, which raises vulnerability and reduces long-term investments. As revenues from natural resources do not require investments into administrative capacity, resource-rich countries tend towards lower state capacity, on average (Besley and Persson, 2014). Moreover, natural resources are often targeted by rebels because of their easy extraction and high monetary value, providing a good source of financing. If rebel groups succeed capturing natural resources, governmental revenues drop sharply, further damaging public goods provision. Hence, the local presence of natural resources may fuel localized conflicts and further increase educational losses.

The level of public goods provision further depends on the ethnic diversity of a population (Habyarimana et al., 2007). A more heterogeneous population represents a greater variety of tastes and preferences, raising the cost of governance as well as the need for cooperation, and resulting in the possible under-provision of public goods. During conflicts, group identification is often used to mobilize fighters, which can further increase the existing social divide and reduce investments into state capacity, worsening the decline in educational provision during crisis.

6.4 Data and empirical strategy

6.4.1 Data sources

Our analysis relies on two main data sources: household data from the DHS program and the geo-referenced conflict event dataset from UCDP. The DHS program offers globally standardized, nationally representative household surveys for a large number of countries including all kinds of socio-demographic characteristics (ICF, 2016). We use the most recent rounds of the standard DHS surveys (2001 to 2016), which include geo-located data on survey location accurate to less than 5 km for most observations (ICF, 2016).[2] Since we measure conflict exposure by direct geodesic distance to the survey location and since distance translates to substantially different travel times in urban as compared to rural areas, we restrict our sample to rural areas of Sub-Saharan Africa only.[3] More importantly, past migration experiences that could potentially bias our estimates downwards by causing us to assign past conflict history to unaffected youth are less prevalent in rural areas than urban areas, as the

[2]DHS randomly displaces the GPS codes of survey locations to secure confidentiality. For most of the clusters, displacement occurs within a radius of 5 km. 1% of the rural clusters is displaced within a radius of 10 km.

[3]Locations are classified as rural or urban by the DHS. The classification is country-specific some based on population size others on infrastructure.

overall migration patterns in Sub-Saharan Africa show a clear rural to urban trend (Awumbila, 2017; IDMC, 2018).[4]

The UCDP geo-referenced Event Dataset (GED, Version 5.0) provides conflict event data for the years 1989 to 2015 (Sundberg and Melander, 2013). It contains information on the date and location of conflict events as well as the estimated number of fatalities. When restricted to Sub-Saharan African countries, the dataset reports 26,970 conflict events for the period of 1989 to 2015.

Additionally, we use precipitation anomalies (at a resolution of 0.5×0.5 decimal degrees) taken from the SPEIbase v.2.5 dataset to control for local weather extremes and the arising shocks to the local economy. The SPEIbase measures precipitation anomalies with a standardized z-score based on monthly precipitation and potential evapotranspiration information (Vicente-Serrano et al., 2010). The geographical information on location of ethnic groups and regional capitals used in the instrumental variable approach is taken from the Nardov Mira geo-referenced ethnic groups (GREG) dataset (Weidmann et al., 2010) and the world map of national capital cities. The GREG dataset is a digital version of the Atlas Narodov Mira showing the geographical location of ethnic groups. It reports 8,969 polygons marking various ethnic homelands. We use the borders of the polygons to measure ethnic diversity and potential inter-ethnic tensions.

For the heterogeneity analysis, income per capita of a country is taken from the Word Development Indicators provided by the World Bank (WorldBank, 2016) and ethnic diversity of a country is measured by the ethnic fractionalization index proposed by Montalvo and Reynal-Querol (2005). To quantify the impact of political quality and democracy, we use the polity2 variable from the Polity IV Project, which ranks a political regime's form of government on a scale ranging from –10 (strong autocracy) to +10 (strong democracy), and is among the most widely used data sources in political science (Marshall et al., 2019). We proxy for local GDP and economic development using satellite data on intensity of nighttime lighting, gathered from the geographic data center of the National Oceanic and Atmospheric Administration's (NOAA) Earth Observatory Group (NOAA, 2019). We use version 4 of the DMSP-OLS Nighttime Lights Time Series, which provides yearly average visible stable lights at cloud free coverage for the years 1992 to 2013 and aggregate it to the resolution of 0.5×0.5 decimal degrees. To identify survey locations rich in natural resources, we utilize the major mineral deposit of the world dataset of the U.S. Geological Survey (USGS) (Schulz and Briskey, 2005). The dataset provides the geographical location of deposits of major non-fuel mineral commodities.

[4] In the sub-sample that record past migration experience, 45% of urban youth live in households that have migrated within the past 25 years, whereas only 29% of rural youth are part of a household that has a migration history.

6.4.2 Measurement

Our outcome variable of interest is educational attainment, which we measure by the reported number of completed school years in the DHS. We determine potential conflict exposure during childhood by combining an individual's birth year with their residence as reported in the survey. We restrict our dataset to individuals born between 1990 and 2003 and thus aged 10 to 26 years at the time of the survey for whom we can observe a full conflict history starting from their pre-birth year.[5]

For our main explanatory variable, we utilize the UCDP dataset. Based on the UCDP's definition, we consider a conflict year to be one in which at least one conflict event took place within a 50 kilometer radius of the survey location.[6] According to this definition, about 12% of all childhood years in the sample were conflict years.

In order to distinguish between the effects of conflicts of varying intensities, we estimate a variety of models by gradually adjusting our definition of a conflict year according to the number of casualties in a given year (based on the best estimate category in the UCDP dataset). We re-define a conflict year as one in which at least one conflict event has taken place within 50 km of the location of interest and in which the conflict events resulted in at least N deaths, with N ranging from 0 to 5,000.[7] We measure potential conflict exposure, C_{jct}, for an individual currently living in location j in country c and born in year t, as follows:

$$C_{jct} = \sum_{\tau=t-1}^{t+12} 1(\text{No. Deaths}_{jc\tau} \geq N); \quad N \in [0, 5000], \tag{6.1}$$

where 1 indicates years in which battle-related deaths in the local neighborhood reached at least N. Total conflict exposure is measured as the sum of all conflict years over the full childhood period, beginning in utero and lasting until the age of 12. We then rank conflict exposure by intensity, using a threshold of 1000 battle-related deaths; conflict years with fewer than 1000 deaths are defined as "moderate-intensity" while years with 1000 or more battle-related deaths are defined as "high-intensity".[8]

For the heterogeneity analyses, we use an alternative measure of conflict intensity by summing up the total number of battle-related deaths and taking the logarithmic transformation, using the inverse hyperbolic sine function. For further analyses, we categorize conflict exposure years by the type of violence, as classified in the UCDP dataset, as well as the critical age periods at which the conflict occurs in an

[5]We only include children starting from the age of 10 years as the multitude of factors determining delays in school entry would confound our regressions for younger children.

[6]Further robustness checks repeat our results for 25, 100 and 200 km.

[7]About 40.5% of all youth in the sample have potentially experienced at least one conflict year of any severity; 11% experienced at least one conflict year with 200 deaths; 5% for conflicts passing the 1,000 deaths threshold and about 2.4% of children experienced conflicts with 5,000 or more deaths.

[8]Only outright civil wars surpass the threshold of 1000 battle-related deaths. Thus, "moderate-intensity conflict" still includes instances of very substantial violence. We distinguish these from instances of starkly extreme violence, labelled as "high-intensity conflict".

individual's life. The UCDP dataset recognizes three distinct categories of violent conflict: (1) state-based conflicts, directly involving a state government; (2) non-state based conflicts, involving violence between two non-governmental organized actors; and (3) one-sided violence against civilians, which can be perpetrated by any organized actor (Sundberg and Melander, 2013). Regarding "critical age periods", we follow the literature and distinguish between in utero (in the year preceding the birth year), early childhood (at age 0 to 3), pre-school age (age 4 to 6) and primary school age (age 7 to 12).[9]

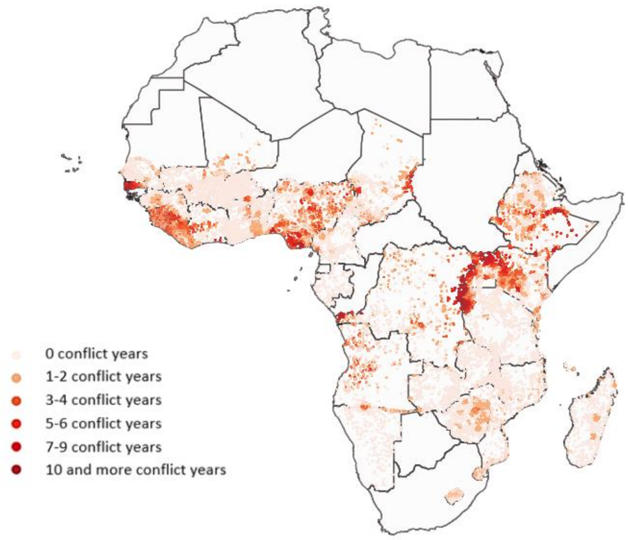
We control for location-specific economic shocks by measuring extreme weather events. We base our extreme weather indicators on the SPEI index, measured at a 12-month scale. Months with SPEI values below –1.5 in a given grid-cell of 0.5 degrees are defined as beeing affected by a drought, and those with SPEI values above 1.5 are defined as being affected by a rainfall shock. The band of +/–1.5 standard deviations is based on the SPI classification system of McKee et al. (1993). We then calculate potential exposure to economic shocks during an individual's childhood as the sum of all past months during which the individual was subjected to drought or rainfall-shock periods separately. We link this grid data to our DHS dataset by choosing the grid cell with the closest centroid to the survey location (within a distance of 200 km).

To analyze the various channels through which conflict may affect education, we first classify countries based on their system of government; countries with polity2 scores below -5 for at least 10 of the included time periods are classified as strong autocracies, while those with polity2 scores above 5 for at least 10 years are classified as democracies. Next, we classify a location as being rich in natural resources if it is located within 50 km of a natural resource deposit. Geographic localities are further categorized based on whether they are above or below median values for ethnic fractionalization, income per capita, and local nighttime light intensity, on average, over time.

Restricting the sample to rural areas results in a dataset of 541,480 observations. Among these observations, 31 countries, 428 regions and 19,652 survey locations are represented. All included surveys are listed in table D.8 in the appendix, and table 6.1 reports summary statistics. Youth in the sample have on average 3.8 years of schooling and about 1.6 years of exposure to any conflict during their childhood. Figure 6.1 maps the average number of conflict years during childhood in all survey locations, whereas figure 6.2 shows the average educational attainment per survey location. Detailed definitions of all variables are displayed in table D.9 in the appendix.

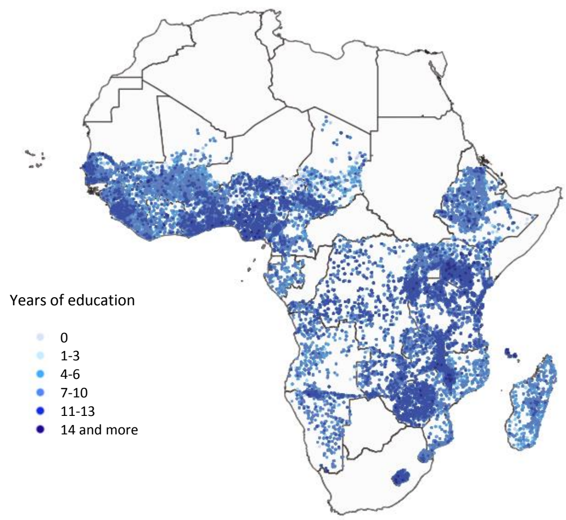
[9] We use the year of birth, as no consistent information is available on the birth month. This introduces measurement error, in particular biasing our estimates on in utero conflict exposure downward.

FIGURE 6.1: Average years of conflict exposure during childhood per survey location



Note: Sources: DHS, UCDP, Map Library.

FIGURE 6.2: Average years of schooling per survey location



Note: Sources: DHS, Map Library.

TABLE 6.1: Summary statistics

Variable	Mean	St. dev.	Min.	Max.
Dependent and main variables				
Years of education	3.81	3.11	0	18
Conflict years	1.64	3.04	0	14
Moderate-intensity conflict years	1.56	2.82	0	14
High-intensity conflict years	0.09	0.43	0	5
Conflict years in utero	0.12	0.33	0	1
Conflict years at age 0–3	0.51	1.08	0	4
Conflict years at age 4–6	0.37	0.82	0	3
Conflict years at age 7–12	0.64	1.37	0	6
Distance to border (in 100 km)	0.25	0.31	0	3
Drought months	11.17	9.87	0	119
Wet months	7.44	8.82	0	71
Age	14.39	3.67	10	26
Female	0.48	0.50	0	1
Heterogeneity analysis				
Asinh(Conflict deaths)	1.95	2.99	0	12.62
Asinh(State conflict deaths)	1.04	2.31	0	10.80
Asinh(Non-state conflict deaths)	0.72	1.75	0	9.06
Asinh(One-sided conflict deaths)	1.34	2.64	0	12.62
Strong democracy	0.24	0.43	0	1
Strong autocracy	0.31	0.46	0	1
Higher ethnic frac.	0.60	0.49	0	1
Higher income	0.47	0.50	0	1
Natural resources	0.22	0.41	0	1
More nightlights	0.50	0.50	0	1
Higher schooling	0.50	0.50	0	1

Note: Descriptive statistics refer to the full sample; $N = 541,480$.

6.4.3 Econometric model

We exploit the spatial and temporal variation in potential conflict exposure to infer the average effect of violent conflicts on educational attainment. Our econometric model regresses the number of years of completed education Y_{ihjct} of an individual i from household h, who is currently residing in survey location j, within country c, and was born in year t, on their potential conflict exposure during childhood C_{jct} (see eq. 6.1) and further controls:

$$Y_{ihjct} \quad = \quad \beta C_{jct} + \mathbf{S}'_{jct}\gamma + \mathbf{X}'_{ihjct}\theta + \lambda_{hæ} + \mu_{ct} + \epsilon_{ihjct}, \tag{6.2}$$

$\mathbf{S}_{jct}$ is a vector that measures the number of months that have resulted in locally relevant (negative) economic shocks. The vector $\mathbf{X}_{ihjct}$ captures a full set of gender-age fixed effects, whereas μ_{ct} denotes country-cohort and $\lambda_{h/j}$ household or location fixed effects. In all specifications, the coefficient β measures the loss in educational attainment due to one additional conflict year of a given severity that the individuals may have experienced during a given childhood period.

Since conflicts do not occur randomly across space and over time, but rather are driven by political and economic causes, these driving factors could themselves be related to educational outcomes. For instance, a weak local labor market reduces the potential outside income of the local population, thereby reducing the opportunity costs of fighting, yet it may also reduce the households' ability and willingness to invest in education and the quality of local public service delivery. If we do not control for the underlying causes of conflict (weak institutions, ethnic tensions, economic shocks, etc.), we may overestimate the disruptive effects of conflict on education.

We address factors driving general conflict dynamics by controlling for an extensive set of fixed effects and further time-variant local controls. The location fixed effects, λ_j, control for all time-invariant differences in local social and economic conditions and the local capacity to deliver education (for 19,652 locations). As several of these factors may also be linked to the likelihood of conflict (like ethnic composition, local institutions, geography, access to infrastructure), factoring out these effects should move us closer to measuring a causal effect. Alternately, household fixed effects, λ_h, are used instead of location fixed effects, restricting the variation even further (for a total of 232,890 households). These control for time-invariant household characteristics and identify the educational losses incurred through conflict by directly comparing youth of distinct ages residing within the same household. Additionally, the country-cohort fixed effects, μ_{ct}, control for yearly changes in the macroeconomic and political environment of each country, including, among others, the country-wide determinants and consequences of violent conflicts and the overall trends in education provision.

Our preferred specifications rely on a combination of these two types of non-nested fixed effects. They identify the effects of conflict based on within-household variation, comparing the educational attainment of different cohorts, living within the same household, who were deferentially exposed to conflict, while at the same time factoring out all common time-varying dynamics that would affect the same cohort across all locations within a country. A remaining source of bias in our estimates comes from time-variant location-specific economic shocks, like major weather shocks, which could potentially affect different parts of a country to varying degrees and which may affect both conflict and educational outcomes. Therefore, in our preferred specifications, we also control for a series of weather shocks, denoted by the vector $\mathbf{S}_{jct}$.

We rely on robust standard errors clustered at the first sub-national administrative level. Alternative specifications in section 6.6 test the robustness of our results to other cluster specifications.

6.4.4 Issues of interpretation

We measure conflict exposure by linking past conflict incidence near a certain locality to the educational attainment of children and youth currently living in that locality. This measure does not capture direct individual exposure to conflict, but rather a location's exposure to conflict. Since particularly high-intensity conflicts are likely to induce massive (although potentially transitory) migration (e.g., Czaika and Kis-Katos, 2009), conflict-exposed youth may not still reside in the same place they lived during the specified age periods. Many may have moved to different locations, at least temporarily, and some of them may not have returned. If migrant youth coming from conflict-affected locations still lag behind in education in their new location, this will lead us to underestimate the effects of conflict on average. Contrary, if children with the best chances to complete their education (e.g., because of showing higher ability or coming from the wealthiest families) are more likely to leave in the face of conflict and/or are less likely to return after the conflict has subsided, our conflict coefficients may be overestimated.[10] Since DHS surveys do not collect information on migration systematically, we are left with a sub-sample of DHS surveys that distinguish between migrant and non-migrant households. In section 6.6, the role of migration in the conflict-education link is analyzed in these two sub-samples.

The potential presence of migration-induced measurement errors cautions us to not interpret our estimates as precise measures of the costs of conflict on education. These limitations notwithstanding, our results have an unambiguous interpretation on the local level. Taking a regional economic approach, our results show how the distribution of human capital in a locality changes with its past conflict history. Local development is most likely to suffer, even in the long run, due to a resulting gap in human capital.

6.5 Results

6.5.1 Exposure to conflicts of different severity

To establish a baseline result, we follow the bulk of the literature by relating individual educational attainment to past exposure to localized conflict events in general. Table 6.2 depicts results from regressing completed years of education on conflict exposure during childhood with a series of different specifications. Column 1 shows the baseline correlation between the years of education and the potential conflict exposure

[10] Children from better socio-economic background suffer more in terms of their education due to conflict (Akresh and De Walque, 2008). This makes it less likely that self-selection into migration drives the negative effects. Nonetheless, the evidence is inconclusive at best.

during childhood, including gender-age, location and birth cohort fixed effects as well as weather shock controls.

TABLE 6.2: Baseline regressions: Conflict exposure and education

Dependent	**Years of education**			
	(1)	(2)	(3)	(4)
Conflict years	-0.057**	-0.059***	0.021	0.018
	(0.024)	(0.021)	(0.017)	(0.017)
Drought months	-0.000	-0.002	-0.006*	-0.006*
	(0.004)	(0.004)	(0.003)	(0.003)
Wet months	-0.010	-0.009	-0.006*	-0.003
	(0.008)	(0.007)	(0.003)	(0.003)
Observations	541,480	480,847	541,480	480,847
R-squared	0.528	0.757	0.550	0.772
Gender-age FE	Yes	Yes	Yes	Yes
Location FE	Yes		Yes	
Birth cohort FE	Yes	Yes		
Household FE		Yes		Yes
Country-cohort FE			Yes	Yes

Note: The table reports OLS estimates of education on the number of past conflict Standard errors are clustered at the level of administrative regions, ***,**,* denote significance at 1, 5 and 10%.

The estimate on conflict shows a negative relationship between conflict exposure and the years of schooling. Exposure to one additional conflict year is linked to about 0.057 fewer years of schooling, or around 1.5% of a standard deviation. This coefficient is statistically significant, but of a rather modest magnitude, and does not suggest substantial losses in education due to conflicts, on average. In column 2 of table 6.2, we substitute the location fixed effects with household fixed effects to control for confounding household characteristics. In doing so, we identify the effects of conflict on education through the distinct potential conflict experiences of youth living within the same household. The results stay the same. Education outcomes may also vary by country and time, since government policies directly shape the school system. Public policies together with national labor market prospects, can be expected to drive individual education-investments decisions while at the same time being correlated with the likelihood of conflict. In order to mitigate this bias, in column 3 we exchange the birth cohort fixed effects for country-specific birth cohort fixed effects. With this approach, we increase the validity of our estimates but lose the ability to identify the average effect of a conflict in a country, as we only focus on within-country differences in conflict exposure driven by the proximity to localized conflicts. In our preferred and most restrictive model in column 4, we combine the country-specific birth cohort fixed effects with the household fixed effects. With the inclusion of country-specific time fixed effects, the conflict coefficient becomes insignificant. This indicates that the broader economic and political shocks that occur at the country level result in a more conflict-prone local environment, and also result in relatively poorer educational outcomes, without us being able to establish a separate link between the variation in local conflict exposure and education.

Our general conflict measure combined a wide range of different types of violence including low-level conflict of short duration (like a violent demonstration) as well as more protracted fighting. The latter can be expected to have a more disruptive effect on education than the former. In order to investigate the distinct effects of conflict on education by conflict intensity, we first classify conflict years into moderate- and high-intensity conflict years based on the threshold of 1000 casualties. The results in table 6.3 confirm our expectations.

TABLE 6.3: Baseline regressions: Intensity of conflict and education

Dependent	Years of education			
	(1)	(2)	(3)	(4)
Moderate-intensity	-0.050**	-0.054**	0.019	0.017
conflict years	(0.024)	(0.021)	(0.017)	(0.017)
High-intensity	-0.162**	-0.135*	-0.161***	-0.116***
conflict years	(0.073)	(0.069)	(0.052)	(0.043)
Observations	541,480	480,847	541,480	480,847
R-squared	0.528	0.757	0.550	0.772
Gender-age FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Location FE	Yes		Yes	
Birth cohort FE	Yes	Yes	Yes	Yes
Household FE		Yes		Yes
Country-cohort FE			Yes	Yes

Note: The table reports OLS estimates of education on the amount of moderate- and high-intensity conflict years at the threshold of 1000 casualties. Standard errors are clustered at the level of administrative regions, ***,**,* denote significance at 1, 5 and 10%.

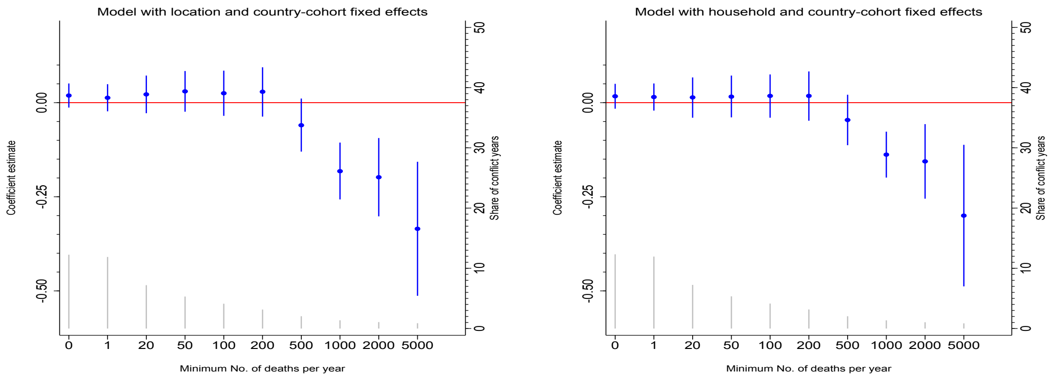
In the first two columns, coefficients on moderate- and high-intensity conflict are both negative and significant, but the point estimates on high-intensity conflicts are about three times larger than those of moderate-intensity conflicts. Once we focus on within-country variation (columns 3 and 4), the significance of moderate-intensity conflicts vanishes, but high-intensity conflicts still stay significantly negative. Our most restrictive model in column 4 shows that while conflict of relatively lower intensity has no effect on the within-country variation in education, a further high-intensity conflict year reduces the number of school years by 0.116 years or 1.4 months.

Figure 6.3 paints a more nuanced picture of the role of conflict severity for education by gradually adjusting our conflict definition to include only conflicts that pass a minimum threshold of yearly casualties (ranging from 1 to 5,000).[11] The left panel is

[11] As only 2.39% of all children in the dataset were subject to a local conflict with more than 5,000 deaths per year, we take this as our upper conflict severity threshold.

based on the specification shown in column 3, whereas the right panel provides the estimates of our preferred regression model (column 4).

FIGURE 6.3: The effects of past conflict exposure on education by conflict severity

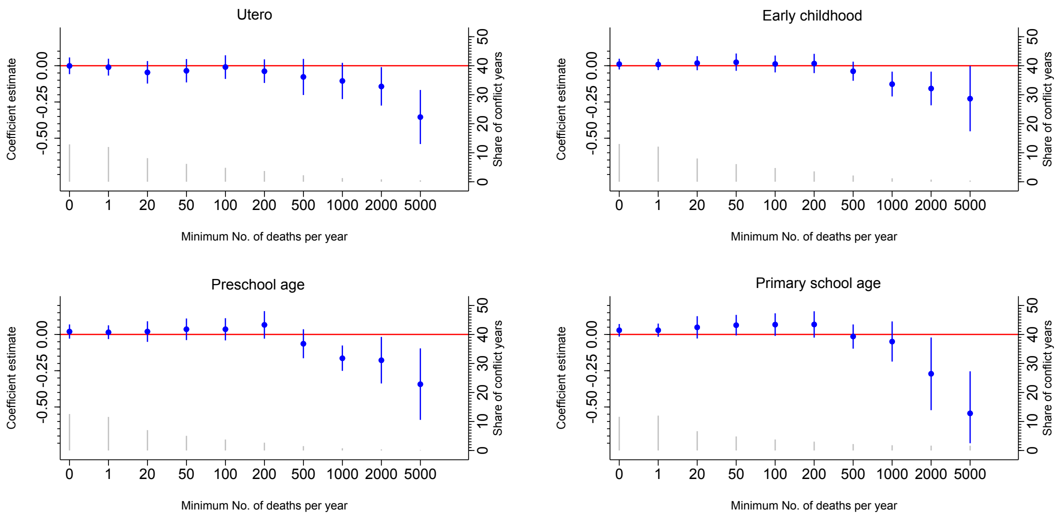


Note: The figure reports point estimates and 95% confidence intervals of education on conflict exposure during childhood within 50 km to the location. Regression specifications column 3 and 4 in table 6.2. The threshold that defines a severe conflict-year varies according to a minimum number of battle-related deaths displayed horizontally. The share of observations with at least one conflict year using the given deaths threshold is depicted by grey bars (second vertical axis). Standard errors are clustered at the level of administrative regions.

The estimates show no negative relationship between moderate-intensity conflict and education. However, high-intensity conflict years reduce the number of years of school attainment. There is a strong gradient, as conflicts of larger severity disrupt education more strongly than conflicts of lower intensity. While exposure to one additional conflict year with at least 500 battle-related deaths reduces education by about 0.05 years, or around 1.6% of a standard deviation, the effect of a conflict year with at least 5,000 deaths amounts to 0.29 years of education lost (9.7% of a standard deviation). The costs of conflict are disproportionately large for those children living in areas with the longest amount of past exposure to conflict. Children in the upper quartile of exposure to at least medium-intensity conflict (500 casualties) have experienced, on average, 2.4 years of such conflicts, resulting in an average education loss of $0.05 \times 2.4 = 0.12$ years, or 1.4 months. Among children in the upper 5% of high-intensity conflict exposure (5000 deaths), the loss amounts to $0.29 \times 2 = 0.58$ years, or around 7 months. These losses appear even more substantial in light of the rather low average educational attainment within our sample (3.8 years). As the difference between the two specifications is marginal, we will focus on the household fixed effects specification in subsequent estimations.

To consider an additional dimension of heterogeneity, we further differentiate the effects of conflict by age at exposure, dividing our conflict measure into those occurring within four distinct age periods in an individual's life: in utero, early childhood, preschool age, and primary school age. Figure 6.4 presents the estimation results. Table D.1 in the appendix shows related results for age-group-wise regressions while distinguishing between moderate- and high-intensity conflicts.

FIGURE 6.4: The effects of conflict on education by severity and age at exposure



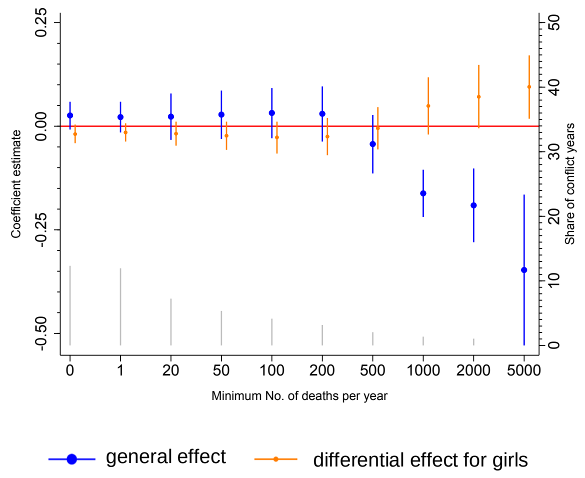
Note: The figure reports estimates of the effect of conflict on education by age periods, whereby age period-specific conflicts enter the regression jointly. Specification as the right panel of figure 6.3.

The results show that severe conflict experiences in all age periods are harmful for educational attainment, whereas exposure to moderate-intensity conflicts does not have statistically significant effects on the number of completed school years.[12] Across the age periods, the effect sizes differ only marginally. Thus, the results reflect educational losses from direct effects of conflict, like school closure or student and teacher absence, and also point to the presence of indirect long-term consequences in line with the early childhood and fetal origin theory (Currie and Almond, 2011; Cunha and Heckman, 2007).

Boys' and girls' education is often found to respond differently to conflict (Shemyakina, 2011). To test for heterogeneity by gender, figure 6.5 shows a common baseline effect that turns more negative with conflict severity, and illustrates a differential effect for females. In our broader sample, high-intensity conflicts reduce the educational attainment of boys more strongly than that of girls. However, there is no marked difference with respect to the effects of moderate-intensity conflict years. Table D.2 in the appendix shows regression results differentiating between moderate- and high-intensity conflict (at the 1000 deaths threshold) by gender. The results show a weakly positive relationship between moderate-intensity conflicts and boys' education, whereas the effect is fully nullified for girls. One additional year of high-intensity conflict leads to 0.19 years less education for boys, but only to a 0.04 years loss for girls. The pattern is similar throughout all age periods (not shown).

[12] As there are only few observations in the age period 7-12 years with high-intensity conflict exposure, the effect is likely under-powered.

FIGURE 6.5: Differential effects of conflict exposure during childhood by gender



Note: The figure reports point estimates and 95% confidence intervals of education on conflict exposure during childhood and the differential effects for girls. Specification as in the right panel of figure 6.3.

6.5.2 Alternative sources of causal identification

Our models reduce the potential for omitted variable bias to a considerable extent, but time-varying local shocks could still drive conflict and education alike. In order to mitigate the possibility of unobservables driving the negative correlation between conflict and education, we extend our fixed effects specifications even further and substitute country-cohort fixed effects with region-cohort fixed effects. These regional birth-cohort fixed effects absorb a wide range of time varying regional characteristics like shocks to the regional labor market or changes in the regional provision of education. They factor out all common variations in both the propensity to experience a conflict and in educational outcomes across administrative regions within the same year. The remaining identifying variation comes from a comparison of locations within the same administrative region of tier one (GADM, 2011) that are within or outside of the direct range of a given conflict. One downside of these specifications is that, they will not be able to capture sufficient across-village variation in outcomes if the administrative units are small or the conflicts relatively far-reaching. Figure D.1 in the appendix presents a full set of results. They show patterns similar to figure 6.3 but with slightly smaller education losses than our main results.

As a second consistency check, we implement an instrumental variable approach to validate our fixed effects results and deal with the potential endogeneity stemming from local time-varying factors. The instrument combines spatial variation in ethnic heterogeneity with the presence of location-specific weather shocks by interacting the distance to the nearest ethnic border with the number of extremely dry and wet months experienced in any location, combining two well-known streams of the literature on the causes of conflict. In economies based on rain-fed agriculture, extreme weather events proxy for economic shocks, determining the likelihood of conflict (Miguel et al., 2004; Harari and Ferrara, 2018). Both extremely dry as well as extremely rainy periods may reduce agricultural income and lower the opportunity costs of fighting. Lower incomes additionally result in lower tax revenues, weakening the state's capacity to fight against insurgencies (Harari and Ferrara, 2018). Unlike in the case of droughts, rainfall-shock months may have further direct effects on conflicts, since floods can act as a barrier to conflict by immobilizing people. Ethnic heterogeneity increases the likelihood that groups compete over power and public goods (Esteban et al., 2012). Often, one group dominates and discriminates against the others, resulting in grievances (Caselli and Coleman, 2013). Ideological differences and incompatible preferences between groups can add to the conflict potential. Moreover, group identification facilitates the mobilization of certain actors, making conflicts more likely.

Both weather shocks and ethnic diversity may directly affect the provision of local public goods, including education. Our regressions control for these direct effects by including localized weather shocks as predictors of education and by factoring out time-invariant spatial heterogeneities, including ethnic diversity, via location or household fixed effects. However, the interaction of weather shocks and ethnic fractionalization should not affect education directly, but rather through a differential effect on conflict potential only, providing us with a viable instrument. We base this instrument on Couttenier and Soubeyran (2014), who find that countries with a higher ethnic fractionalization are more prone to conflict when affected by a drought than less ethnically fractionalized countries, experiencing a similar drought. The instrument identifies the effects of conflict through the heterogeneous effect of a local economic shock, dependent on the risk of conflict due to ethnic fractionalization. The exclusion restriction behind this instrument requires that education be more negatively affected by weather shocks in ethnically heterogeneous regions due solely to the increased conflict potential arising from ethnic heterogeneity and not because of other factors. One potential confounding factor could arise if the distance to ethnic borders measures not only ethnic heterogeneity but also remoteness from district administrative offices, which could affect the government's ability to respond to localized shocks. To test for this alternative channel, we present results controlling for the distance between a location and the nearest administrative center, interacted with weather shocks.

The first and second stage regression results are reported in table 6.4. We use our baseline conflict measure (total number of conflict years of any severity) as weather shocks may result in conflicts of mild to moderate to severe intensity alike (Hendrix and Salehyan, 2012).

Weather shocks can serve to trigger conflicts and are thus a good predictor of conflict occurrence. However, the role of weather shocks in influencing the quantity of conflict fatalities is weak. Hence, in this step we use instruments only to test the link between past conflict events and education, without distinguishing conflicts by their severity.

TABLE 6.4: Instrumental variable approach: Conflict exposure and education

		FIRST STAGE		
Dependent		**Conflict years**		
	(1)	(2)	(3)	(4)
Instruments:				
Distance to border × Drought months	-0.024***	0.002	-0.021***	0.002
	(0.003)	(0.002)	(0.003)	(0.002)
Distance to border × Wet months	-0.021***	-0.013***	-0.020***	-0.012***
	(0.004)	(0.003)	(0.003)	(0.002)
Controls:				
Drought months	0.015***	0.000	0.020***	0.000
	(0.002)	(0.001)	(0.002)	(0.002)
Wet months	-0.012***	0.001	-0.025***	-0.004
	(0.002)	(0.002)	(0.003)	(0.002)
Distance to admin. center × Drought months			-0.006***	0.000
			(0.001)	(0.001)
Distance to admin. center × Wet months			0.015***	0.006**
			(0.002)	(0.002)
R-Squared	0.954	0.977	0.954	0.977
Kleinbergen-Paap F-stat.	52.64	13.67	45.17	12.37
		SECOND STAGE		
Dependent		**Years of education**		
Conflict years	-0.374***	-0.456	-0.397***	-0.401
	(0.127)	(0.327)	(0.143)	(0.347)
Drought months	0.000	-0.005***	0.003	-0.001
	(0.002)	(0.002)	(0.003)	(0.002)
Wet months	-0.015***	-0.005**	-0.017***	-0.004
	(0.003)	(0.002)	(0.005)	(0.003)
Distance to admin. center × Drought months			-0.003*	-0.004***
			(0.002)	(0.001)
Distance to admin. center × Wet months			0.001	-0.001
			(0.003)	(0.003)
Observations	480,847	480,847	480,847	480,847
R-squared	0.753	0.767	0.752	0.769
Household FE	Yes	Yes	Yes	Yes
Gender-age FE	Yes	Yes	Yes	Yes
Birth cohort FE	Yes	Yes	Yes	Yes
Country-cohort FE		Yes		Yes

Note: The table reports the first and second stages from the IV regressions of education on the number of conflict years. Standard errors are clustered at the survey location. ***,**,* denote significance at 1, 5 and 10%.

Column 1 presents results for regressions using gender-age, household, and birth-cohort fixed effects, whereas in column 2 birth-cohort fixed effects are replaced by country-specific birth-cohort fixed effects. Standard errors are clustered at the location level. In column 1 of the first stage, drought events increase the likelihood of conflict, on average, and the effect diminishes with the distance to an ethnic border, highlighting the heterogeneous effect of droughts as expected. By contrast, rainfall-shocks seem to act as a barrier to conflict, reducing the average conflict potential. This reduction is stronger in locations farther away from ethnic borders. The inclusion of country-specific birth-cohort fixed effects in column 2 absorbs the general effect of the extreme weather shocks, indicating that they have a national rather than a local scope. The interaction effect with rainfall-shock months still survives, showing that rainy periods reduce conflict potential more in ethnically homogeneous areas. Our results are closely related to O'Loughlin et al. (2012), which shows that climate conditions have effects at the local and national level. In columns 3 and 4, we add interaction terms of our weather variables with the distance to the regional capital to ensure that our instrument does not merely capture the effects of remoteness. In remote areas, the infrastructure is often less developed and aid programs may take longer to reach the affected population, increasing the impact of the weather effects. At the first stage, rainfall-shock months tend to increase the likelihood of conflict more in remote areas, underlining the immobility argument.

At the second stage, one further conflict year during childhood reduces educational attainment by 0.374 years (column 1) which is substantially larger than the OLS estimate (-0.059). The difference could arise from a reduction in measurement errors or omitted variables. When interpreting the IV estimates as local average treatment effects, educational losses are especially large for conflicts arising from agricultural shocks triggered by weather anomalies combined with ethnic fractionalization. The estimated effects are highly significant when only cohort-fixed effects are included. They stay of similar magnitude but lose their significance when we include country-specific birth cohort fixed effects. The inclusion of the interactions between weather events and the distance to the regional capital (column 3) does not change our estimates of conflict effects, making us more confident that the instruments measure the effects of conflict potential and not merely remoteness.

The IV estimates are of larger magnitude and still negative, supporting our OLS results. Once we control for country-specific variation over time, the relationship between our generic measure of conflict exposure and educational attainment is insignificant, showing that location-specific conflict occurrence does not affect educational attainment, on average. As weather shocks combined with ethnic fragmentation only provide a viable instrument for conflict occurrence and do not predict conflict intensity, we cannot use the same procedure to analyze the effects of high-intensity conflicts. However, we believe that our OLS results on higher intensity conflict are also more likely to underestimate the educational costs of conflict.

6.5.3 State capacity and further mechanisms

How much a conflict impairs the educational attainment of local children also depends on the actors involved in the conflict. As providers of education, governments have an incentive to maintain a functional education system, whereas non-state actors may destroy schools. Hence, we would expect that non-state conflicts have a stronger negative effect on education than state-based conflicts. Following the UCDP classification, we divide conflicts into state-based, non-state based, and one-sided violence. We regress the years of education on these three distinct types of conflict, including our standard controls. We focus on a summary measure of conflict intensity, following the conflict literature, by using the inverse hyperbolic sine of the number of casualties of the respective conflict type. This helps us to incorporate the heterogeneous effects by conflict severity and reduce the number of presented interactions in a concise manner. Additionally, it is easily interpretable and avoids the placement of arbitrary thresholds. Using our preferred specification, table 6.5 shows that on average the log-transformed number of casualties is not significantly related to the years of education. But, this measure still allows heterogeneous effects by the conflict actors. Most importantly, the loss of education seems to be caused by non-state conflicts, confirming our expectations. We find no significant effect of conflict severity on education for state-based conflicts and one-sided violence. A potential explanation for this latter null result is that attacks on civilians are, on average, of a lower intensity and usually accompany other conflicts involving state- or non-state actors.[13]

TABLE 6.5: Heterogeneous effects of conflict intensity on education by conflict type

	Years of education				
	(1)	(2)	(3)	(4)	(5)
Asinh(Conflict deaths)	-0.006				
	(0.011)				
Asinh(State conflict deaths)		0.016			0.017
		(0.015)			(0.016)
Asinh(Non-state conflict deaths)			-0.048**		-0.049**
			(0.021)		(0.021)
Asinh(One-sided conflict deaths)				0.003	-0.001
				(0.014)	(0.015)
Observations	480,847	480,847	480,847	480,847	480,847
R-squared	0.772	0.772	0.772	0.772	0.772

Note: The table reports OLS estimates of education on the the inverse hyperbolic sine function of the number of casualties during childhood of distinct conflict types. Specifications include gender-age, country-cohort and household fixed effects and weather controls. Standard errors are clustered at the level of administrative regions. ***,**,* denote significance at 1, 5 and 10%.

In a next step, we analyze a series of factors which potentially moderate the effects of conflict on education, distinguishing between a set of country and location characteristics. Results are presented in table 6.6. All characteristics are interacted with past conflict intensity (the inverse hyperbolic sine of the number of casualties) one-by-one first, whereas column 6 specifies the model to include all factors together.

[13]The correlation of one-sided violence and state-based conflict is especially high with $\rho = 0.78$.

TABLE 6.6: Heterogeneous effects of conflict intensity on education by country and location characteristics

	Years of education					
	(1)	(2)	(3)	(4)	(5)	(6)
Asinh(Conflict deaths)	-0.067**	0.008	-0.008	-0.001	0.005	-0.036
	(0.034)	(0.013)	(0.011)	(0.012)	(0.013)	(0.033)
... × Strong democracy	-0.019					-0.030
	(0.020)					(0.020)
... × Strong autocracy	0.076**					0.078**
	(0.032)					(0.032)
... × Higher ethnic frac.		-0.022				-0.036*
		(0.020)				(0.019)
... × Higher income per capita			0.008			0.018
			(0.026)			(0.027)
... × Natural resources				-0.027*		-0.026*
				(0.014)		(0.014)
... × More nightlights					-0.020*	-0.015
					(0.012)	(0.011)
Observations	480,847	480,847	480,847	480,847	480,847	480,847
R-squared	0.772	0.772	0.772	0.772	0.772	0.772

Note: The table reports OLS estimates from education on the inverse hyperbolic sine function of the number of casualties during childhood and its interaction with country and location characteristics. Specifications as in table 6.5. ***,**,* denote significance at 1, 5 and 10%.

We expect that educational losses from conflict vary with the form of government in power at the time of conflict. Classifying countries into strong autocracies, strong democracies, and others, column 1 of table 6.6 shows that the number of fatalities in a conflict decreases local school attainment both in weak states and strong democracies. As only few strong democracies exist in our sample, and these countries have not participated in large-scale conflicts, it is likely that these estimates are under-powered.[14] There is no educational loss in strong autocracies due to conflict confirming our hypothesis.

The provision of public goods may be more negatively impacted by conflict in ethnically heterogeneous states than homogeneous ones, as cooperation costs generally increase with heterogeneity. Similarly, states with a poorer population (measured by lower average income) may face larger financial restrictions and be more susceptible to crisis due to their budget constraints. We test these channels in columns 2 and 3 of table 6.6. Both results turn out to be insignificant. Hence, conflict intensity is not significantly differentially linked to educational losses in more ethnically fractionalized or poorer states, on average.

At the local level, natural resources are often targeted by rebel groups because of their easy extraction and their high monetary value. If rebel groups succeed in capturing natural resources, government revenues drop sharply, reducing public

[14]We classified Benin, Lesotho, Madagascar, Malawi, Mali and Namibia as strong democracies. These countries did not experience any conflict of high intensity.

goods provision. Consequently, the educational attainment of children from resource-rich regions is likely to suffer more due to conflict. Results in column 4 of table 6.6 support the resource curse argument. Educational losses significantly increase with conflict intensity in locations with natural resource deposits.

Local economic development may also be a relevant factor in education as the local demand for education and the local ability to provide public education can be expected to rise with local economic development. Similarly, wealthier regions with higher initial levels of educational attainment may face larger potential decreases if education is disrupted by conflict. Hence, the direction of the effect is a priori unclear. Our estimate in column 5 of table 6.6 shows a negative effect of conflict intensity in regions with higher economic prosperity. This indicates that, ceteris paribus, better-developed regions lose more education due to conflict.

Column 6 of table 6.6 includes all interactions, jointly testing heterogeneities at the country level and at the local level against each other. In this specification, our proxy for the state capacity channel turns out to be the most relevant differentiating factor. Education suffers substantially less from higher intensity conflicts in strong autocracies than under any other conditions. Regions with higher ethnic diversity are more strongly affected by conflict in terms of lost education, indicating that public service provision during times of conflict may be more limited in ethnically-heterogeneous countries. All else equal, geographic localities closer to natural resource deposits suffer substantially larger educational losses than geographic localities farther away. This indicates that a local resource curse not only serves to trigger conflicts, but also interacts with conflict intensity in affecting educational losses. Finally, the coefficient for local nighttime light intensity becomes insignificant in this joint test.

6.6 Further robustness issues

Our measurement strategy relies on the assumption that we can assess the past conflict exposure of an individual by measuring past conflict occurrences near the individual's current geographic location. Thereby, we neglect the potential measurement errors from migration described in section 6.4.4. Although we cannot analyze the role of migration in the whole sample, we observe migration patterns within a sub-sample of the population.[15] In this sub-sample, the share of migrants in the total youth population is positively correlated with years of past conflict exposure (over the last 25 years) for high intensity conflicts (see table D.3 in the appendix), but are uncorrelated with conflict in general, or moderate-intensity conflicts. Hence, our estimates for high-intensity conflicts may be more prone to a bias due to incorrectly assigned birthplaces. With respect to self-selection into migration, migrants are, on average, better educated and tend to live in wealthier and better educated households than

[15]This sub-sample includes data from 20 countries.

non-migrants (see D.4 in the appendix), suggesting that there may be a downward bias in the high-intensity conflict estimates.

In the migration sub-sample, we can directly compare the conflict coefficients by migration status. Table D.5 replicates our baseline results for the sub-sample of youth with migration information. Even though the sample is reduced substantially (to 68,110 observations), we can still see the same link between exposure to conflicts of high intensity and losses in education in column 1. In the model with household fixed effects, we run into power issues, as the sample is further reduced by half (column 2). The substantially smaller sample size renders the resulting coefficient estimates insignificant. However, the magnitude and direction of the effect are both comparable to the first specification. In columns 3 and 4, we estimate the general effect of past conflict exposure together with a differential effect for non-migrants. Migrants indeed show worse education outcomes than non-migrants in locations exposed to moderate-intensity conflicts, so migration may contribute to our estimate of the local costs of moderate-intensity conflict. However, in locations which have experienced a high-intensity conflict, non-migrants have decidedly fewer years of education on average, indicating that migration is not the only factor driving our results. Overall, migrants seem to be better off than locals. This could be because families who care more about education are more likely to relocate before the outbreak of a conflict, thereby reducing the human capital of the local population. Alternately, post-conflict locations might attract relatively better-educated households. In either case, migration tends to lead to an underestimation of the individual costs of high-intensity conflict.

Since the timing and location of conflicts are not exogenous, further placebo checks can help us to assess the potential role of pre-trends or other confounding factors driving local conflict and education. For this, we repeat our baseline regressions linking conflict exposure to education, but focus on conflicts that should not have directly affected children and youth in our sample, due to the nature of their timing. As a first test, we regress individual years of education on conflict occurring in the third and second year before the birth of a child. The results are shown in table D.6. There is no residual correlation between late-life educational attainment and pre-utero exposure to conflict even among high-intensity conflicts. It follows that, the correlation between educational attainment and conflict exposure is unlikely to be driven by pre-trends. As a second placebo test, we examine educational attainment among those who were exposed to localized violence as adults, during a time when they were likely to have already finished their secondary education. For this, we focus on a sample of adults aged 26 to 47 (born between 1969 and 1986), and test for correlation between their potential for conflict exposure between the ages of 20 and 25 and their completed years of education. The results in column 3 and 4 of table D.6 show no significant negative coefficients, and coefficients for moderate-intensity conflicts in fact depict a positive correlation, indicating that our previous findings are unlikely to be driven by common underlying trends.

Throughout all of our analyses, we reported estimates with standard errors clustered at the regional level, allowing for unspecified correlation between the residuals of individuals living in the same region. However, in our context, the correct level of clustering is debatable. Since we are measuring conflict exposure by location, measurement errors should similarly affect all individuals living within a certain location. Hence, standard errors should at least be clustered at the locality level. The presence of correlation at a larger level of analysis, for instance at the regional or even national level, is plausible and partially captured via our fixed effects. To check for the robustness of our results to the level of clustering, we compare our main specifications using three additional steps. Columns 1 and 2 in table D.7 report regression results with standard errors clustered at the locality level, allowing only for correlation within specific locations. Columns 3 and 4 report results with two-way clustering at the locality level and among country-birth cohort cells. This latter method relies on asymptotics in the lowest level clusters, and is the most appropriate method to use when there is within-correlation on both dimensions and each dimension has many clusters (Cameron and Miller, 2015). Columns 5 and 6 report results using spatial standard errors, which correct for spatial dependence in the error terms. Since we measure conflict exposure within a 50 km radius around the location, neighboring locations will likely be affected by the same conflicts. In order to take this into account, we run regressions with spatially corrected standard errors based on Conley (1999), correcting for spatial correlation within 100 km to the survey location. The distinct versions of clustering do not change our main results substantially.

In our analysis, we assigned each conflict event to all survey locations located within a 50 km radius to the conflict. However, the average influence area of a conflict could be both farther or nearer. Therefore, we re-estimate the effects of conflicts using different severity thresholds for conflict influence zones, namely 25, 100 and 200 km. The results are shown in figure D.2 in the appendix. Consistent with the literature (see e.g., Hallberg, 2012), the 25 km distance measure does not seem to sufficiently capture the full area of a conflict, and results yield substantially larger standard errors. However, effect sizes diminish when using wider distance measures of up to 200 km. As expected, the impact on educational attainment declines as the distance to the original conflict event increases.

6.7 Conclusion

We study the link between localized conflict occurrence and educational attainment of children in 31 Sub-Saharan African countries from 1989 to 2015. In doing so, we are able to generalize the results of a large number of case studies on this link, and investigate heterogeneous effects of different conflict types as well as context-specific conflict characteristics. For this purpose, we combine DHS surveys with the UCDP geo-referenced conflict dataset and link individual school attainment of youth to local occurrence of conflicts during four specific age periods during childhood. We address the endogeneity of conflict across time and space by including two-way fixed effects for households and country-specific birth cohorts, capturing time-variant shocks to conflict and education at the country level and time-invariant differences in the propensity of conflict across households. Additionally, we control for location-specific weather shocks and implement an instrumental variable approach to address further time-varying confounders.

Although we cannot identify robust effects from our generic conflict exposure, which measure includes every type of conflict event, the most severe and prolonged conflicts do result in substantial average costs of educational attainment. Educational losses occur mainly in states with weaker governance, which are more likely to experience declines in state capacity due to a conflict. Losses are also mainly triggered by non-state conflicts, which are more likely to destroy school infrastructures and thus harm the administrative capacity of the government. This highlights the crucial role of state capacity in mediating the effects of conflict on education. Moreover, conflict exposure during all age periods harms education, and the educational outcomes of boys are more strongly affected by high-intensity conflicts than those of girls.

The results document longer lasting losses of education among youth cohorts currently living in locations previously affected by a high-intensity conflict. Although we cannot distinguish direct disruptions to education from human capital losses through the channel of out-migration of those more likely to receive an education, we document shifts in the human capital composition of localities previously affected by severe conflict, leading to economic and social costs in the long run. Contextualizing the findings of previous case studies, the paper highlights the diverse effects of conflict on education. We confirm heterogeneous effects by conflict severity and age at conflict exposure found by previous literature. With respect to gender, our results show a stronger negative effect for girls in moderate-intensity conflicts and a smaller effect in high-intensity conflicts compared to boys, potentially consolidating the differential effects found in previous literature. We add new dimensions of heterogeneity by investigating conflict types as well as location and country characteristics, especially highlighting the role of state capacity in the link between conflict and education. In order to achieve universal education for all, remedial policy interventions should target previously conflict-affected regions, especially in areas where state capacity is limited.

Chapter 7

Conclusion

This thesis has dealt with the causes and consequences of conflict, helping toward understanding violent conflict. Contributing to the recent micro-economic literature, the empirical papers of the dissertation identify two causes and two consequences of violent conflict.

For a better understanding of the roots of conflict, chapter 3 and 4 establish a causal link between political favoritism as well as water scarcity and conflict. The results in chapter 3 show that political favoritism reduces the intensity of violent conflict in the home regions of political leaders in autocracies while they are in power. The effect is strongest in regimes with a high likelihood of engaging in coup-proofing strategies. Chapter 4 provides empirical evidence for the Homer-Dixon model. We find that a rise in the scarcity of water is increasing the risk of conflict. The effect is substantially alleviated by access to groundwater.

Chapter 5 and 6 elaborate on the consequences of conflict with respect to social segregation and education. In chapter 5, we find that non-discriminatory behavior coexists with discriminatory feelings of prejudice and fear towards ex-combatants in post-conflict Colombia. The mediated contact has promoted positive attitudes towards reintegrating ex-combatants and increased monetary support once crucial skills were highlighted. Chapter 6 concludes that the educational consequences of conflict are strongly context-dependent. Educational losses are strongest in states with poor governance and in highly intense conflicts fought by non-governmental actors.

Based on the empirical findings presented in this thesis and the existing literature on the causes and consequences of conflict, two main conclusions emerge.

First, countries are trapped in vicious circles of conflict. The identified consequences of conflict simultaneously present causes of conflict, providing a potential explanation why they are strongly geographically clustered and persistent. As discussed in chapter 5, societies may be segregated by civil wars. If not addressed, this segregation provides breeding ground for further conflicts (in post-conflict societies) (Esteban et al., 2012). Moreover, conflict hinders social and economic development and consolidates existing grievances (Gates et al., 2012), for instance, by the interruption of human capital accumulation as shown in chapter 6. In turn, multiple factors closely associated with underdevelopment, for example human capital, cause conflict (Blattman and Miguel, 2010). The clear connection between violent conflict and underdevelopment shows that the global challenges, which the international community is facing, are interwoven. This provides two entry points for policymakers to break the conflict trap: policymakers can focus on the termination of conflict with conflict resolution and peace-building activities, or they can address the structural factors causing conflict, mainly underdevelopment and associated factors. Both approaches are valid and most likely a combined strategy is advisable. The call of a new direction by 'Pathways to Peace', however, shows that existing peace-building activities and conflict resolution efforts have not brought the success expected (World Bank Group, 2018). Concerns about the effectiveness of such activities was also raised by others (Anderson et al., 2007). Rather than shutting down these activities, the effectiveness of peace-building and conflict resolution initiatives should be improved by critically evaluating the activities and assisting research. The rather limited amount of research on peace-building and conflict resolution leaves ample scope for improvement.

The second main conclusion is that governance and state capacity play a crucial role in the connection between violent conflict and the structural factors causing it. The empirical findings presented in this thesis provide support for this statement. First, governments impact the costs of fighting, by augmenting the amount of resistance and security precautions in the country, or by altering the penalties on violent felonies. This is shown in chapter 3, where favored home regions of autocratic leaders, which receive more protection and attention by the government, experience lower conflict intensity. Second, governments can shape the incentives to fight by promoting social and economic well-being of their citizens and addressing other causes of conflict. This includes reducing the vulnerability to climate-related shocks, which spur conflict (see chapter 4). Moreover, as shown in chapter 6, governments can alleviate the consequences of conflict by successful crisis management, maintaining adequate public goods provision. But, governments also directly affect the risk of conflict by initiating violence or being the cause of conflict when misusing their power. This phenomenon has received only few attention in the conflict literature. I join Blattman and Miguel (2010) in encouraging research in this field. As chapter 3 shows, good institutions that include checks and balances help to limit the misuse of power by politicians. Taken together, governments can play a key role in preventing conflicts and alleviating their consequences. Yet, one needs to admit that in order to undertake such actions, financial and organizational resources are necessary. These are often lacking among others as a result of conflict (Goldstone, 2008). Development aid that targets the improvement of governance capabilities and the recovery of state legitimacy can support to overcome the conflict trap (Brinkerhoff, 2007). This provides a third entry point to break the vicious circle.

On a methodological level, the interdependence of conflict and the structural factors linked to conflict impedes the identification of causal effects. Therefore, attention should be paid to causal identification and unidentified studies should be taken with caution. Thereupon, the economic research can make a significant contribution to the conflict literature.

In summary, countries are trapped in a vicious circle of conflict, explaining the recurrence and persistence of violence. There are three entry points to break this circle. In all of them, policymakers hold a leading role. Future work could focus on evaluating the diverse, implemented policies targeting the termination and prevention of conflict. This would provide policymakers with feedback, and improve the effectiveness of peace building and maintaining initiatives.

Bibliography

Acemoglu, D., T. Verdier, and J. A. Robinson (2004). Kleptocracy and divide-and-rule: A model of personal rule. *Journal of the European Economic Association 2*(2-3), 162–192.

Afrobarometer (2019). Merged data rounds 1–6. Dataset. `http://www.afrobarometer.org` [accessed on 10.01.2019].

Akbulut-Yuksel, M. (2014). Children of war: The long-run effects of large-scale physical destruction and warfare on children. *Journal of Human Resources 49*(3), 634–662.

Akresh, R. and D. De Walque (2008). Armed conflict and schooling: Evidence from the 1994 rwandan genocide. IZA Discussion paper 3516, Bonn. Institute of Labor Economics.

Akresh, R., L. Lucchetti, and H. Thirumurthy (2012). Wars and child health: Evidence from the eritrean–ethiopian conflict. *Journal of Development Economics 99*(2), 330–340.

Al Ramiah, A. and M. Hewstone (2013). Intergroup contact as a tool for reducing, resolving, and preventing intergroup conflict: evidence, limitations, and potential. *American Psychologist 68*(7), 527.

Allport, G. (1954). *The nature of prejudice*. MA: Perseus Books.

Almer, C., J. Laurent-Lucchetti, and M. Oechslin (2017). Water scarcity and rioting: Disaggregated evidence from sub-saharan africa. *Journal of Environmental Economics and Management 86*, 193–209.

Almond, D. and J. Currie (2011). Killing me softly: The fetal origins hypothesis. *Journal of Economic Perspectives 25*(3), 153–172.

Anderson, C. A. (1989). Temperature and aggression: ubiquitous effects of heat on occurrence of human violence. *Psychological Bulletin 106*(1), 74.

Anderson, M. B., D. Chigas, and P. Woodrow (2007). Encouraging effective evaluation of conflict prevention and peacebuilding activities: Towards dac guidance. *OECD Journal on Development 8*(3), 3–102.

Angrist, J. and A. B. Krueger (1994). Why do world war ii veterans earn more than nonveterans? *Journal of Labor Economics 12*(1), 74–97.

Angrist, J. D. (1990). Lifetime earnings and the vietnam era draft lottery: evidence from social security administrative records. *The American Economic Review*, 313–336.

Annan, Jeanette, B. C. (2010). The consequences of child soldiering. *The Review of Economics and Statistics 94*(4), 882–898.

Annan, J., C. Blattman, D. Mazurana, and K. Carlson (2011). Civil war, reintegration, and gender in northern uganda. *Journal of Conflict Resolution 55*(6), 877–908.

Arbatli, C. E., Q. H. Ashraf, O. Galor, and M. Klemp (2020). Diversity and conflict. *Econometrica 88*(2), 727–797.

Arcand, J.-L. and E. D. Wouabe (2009). Households in a time of war: Instrumental variables evidence for angola. Working paper, The Graduate Institute, Geneva.

Armand, A., P. Atwell, and J. F. Gomes (2020). The reach of radio: Ending civil conflict through rebel demobilization. *American Economic Review 110*(5), 1395–1429.

Åse, C. and M. Wendt (2018). Gendering the new hero narratives: Military death in denmark and sweden. *Cooperation and Conflict 53*(1), 23–41.

Asher, S. and P. Novosad (2017). Politics and local economic growth: Evidence from india. *American Economic Journal: Applied Economics 9*(1), 229–73.

Awumbila, M. (2017). Drivers of migration and urbanization in africa: Key trends and issues. Report, United Nations Secretariat, Population Division, USA, New York.

Bagues, M. and B. Esteve-Volart (2016). Politicians' luck of the draw: Evidence from the spanish christmas lottery. *Journal of Political Economy 124*(5), 1269–1294.

Balk, D. L., U. Deichmann, G. Yetman, F. Pozzi, S. I. Hay, and A. Nelson (2006). Determining global population distribution: methods, applications and data. *Advances in Parasitology 62*, 119–156.

Barker, D. J. (1995). Fetal origins of coronary heart disease. *BMJ: British Medical Journal 311*(6998), 171.

Basedau, M., B. Pfeiffer, and J. Vüllers (2016). Bad religion? religion, collective action, and the onset of armed conflict in developing countries. *Journal of Conflict Resolution 60*(2), 226–255.

Bauer, M., C. Blattman, J. Chytilová, J. Henrich, E. Miguel, and T. Mitts (2016). Can war foster cooperation? *Journal of Economic Perspectives 30*(3), 249–74.

Bauer, M., N. Fiala, and I. Levely (2017). Trusting former rebels: An experimental approach to understanding reintegration after civil war. *The Economic Journal 128*(613), 1786–1819.

BBC (2015). Tikrit: Iraq's city of palaces. News report, BBC News. `https://www.bbc.com/news/world-middle-east-31850648` [accessed on 27.10.2020].

Becker, G. (1971). *The economics of discrimination*. University of Chicago Press.

Bekkers, R. and P. Wiepking (2011). Who gives? a literature review of predictors of charitable giving part one: religion, education, age and socialisation. *Voluntary Sector Review 2*(3), 337–365.

Bellows, J. and E. Miguel (2009). War and local collective action in sierra leone. *Journal of Public Economics 93*(11–12), 1144–1157.

Berger, M. C. and B. T. Hirsch (1983). The civilian earnings experience of vietnam-era veterans. *Journal of Human Resources*, 455–479.

Berman, N., M. Couttenier, D. Rohner, and M. Thoenig (2017). This mine is mine! how minerals fuel conflicts in africa. *American Economic Review 107*(6), 1564–1610.

Bertoni, E., M. Di Maio, V. Molini, and R. Nistico (2019). Education is forbidden: The effect of the boko haram conflict on education in north-east nigeria. *Journal of Development Economics 141*, 102249.

Bertrand, M. and S. Mullainathan (2005). Implicit discrimination. *American Economic Review 95*(2), 94–98.

Besley, T. and T. Persson (2010). State capacity, conflict, and development. *Econometrica 78*(1), 1–34.

Besley, T. and T. Persson (2014). The causes and consequences of development clusters: State capacity, peace, and income. *Annual Review of Economics 6*(1), 927–949.

Betancourt, T. S., J. Agnew-Blais, S. E. Gilman, D. R. Williams, and B. H. Ellis (2010). Past horrors, present struggles: The role of stigma in the association between war experiences and psychosocial adjustment among former child soldiers in sierra leone. *Social Science and Medicine 70*(1), 17–26.

Bharadwaj, P. and T. S. Vogl (2016). Crisis and human biology. In J. Komlos and I. R. Kelly (Eds.), *The Oxford Handbook of Economics and Human Biology*, pp. 52–69. Oxford: Oxford University Press.

Blattman, C. (2009). From violence to voting: War and political participation in uganda. *American Political Science Review*, 231–247.

Blattman, C. and E. Miguel (2010). Civil war. *Journal of Economic Literature 48*(1), 3–57.

Breckner, M. and U. Sunde (2019). Temperature extremes, global warming, and armed conflict: new insights from high resolution data. *World Development 123*, 104624.

Brinkerhoff, D. W. (2007). *Governance in post-conflict societies: Rebuilding fragile states*. Routledge.

Brück, T., M. Di Maio, and S. H. Miaari (2019). Learning the hard way: The effect of violent conflict on student academic achievement. *Journal of the European Economic Association 17*(5), 1502–1537.

Brückner, M. (2010). Population size and civil conflict risk: is there a causal link? *The Economic Journal 120*(544), 535–550.

Bruederle, A. and R. Hodler (2018). Nighttime lights as a proxy for human development at the local level. *PloS one 13*(9).

Brunner, E., S. L. Ross, and E. Washington (2011). Economics and policy preferences: causal evidence of the impact of economic conditions on support for redistribution and other ballot proposals. *Review of Economics and Statistics 93*(3), 888–906.

Burgess, R., R. Jedwab, E. Miguel, A. Morjaria, and G. Padró i Miquel (2015). The value of democracy: evidence from road building in kenya. *American Economic Review 105*(6), 1817–51.

Burke, M., S. M. Hsiang, and E. Miguel (2015). Climate and conflict. *Annual Review of Economics 7*, 577–617.

Callen, M., M. Isaqzadeh, J. D. Long, and C. Sprenger (2014). Violence and risk preference: Experimental evidence from afghanistan. *American Economic Review 104*(1), 123–48.

Camerer, C. (2011). The promise and success of lab-field generalizability in experimental economics: A critical reply to levitt and list. *SSRN 1977749*.

Cameron, A. C. and D. Miller (2015). A practitioner's guide to cluster-robust inference. *Journal of Human Resources 50*(2), 317–372.

Caramés, A., V. Fisas, D. Luz, and M. Maixenchs (2006). Sierra leone. Discussion paper, Escola de Pau, Barcelona.

Carozzi, F. and L. Repetto (2016). Sending the pork home: Birth town bias in transfers to italian municipalities. *Journal of Public Economics 134*, 42–52.

Caselli, F. and W. J. Coleman (2013). On the theory of ethnic conflict. *Journal of the European Economic Association 11*(suppl_1), 161–192.

Chambers, D. P. and J. A. Bonin (2012). Evaluation of release-05 grace time-variable gravity coefficients over the ocean. *Ocean Science 8*(5), 859.

Chen, Y., H. Li, and L.-A. Zhou (2005). Relative performance evaluation and the turnover of provincial leaders in china. *Economics Letters 88*(3), 421–425.

Choi, J.-K. and S. Bowles (2007). The coevolution of parochial altruism and war. *Science 318*(5850), 636–640.

CIA (2016). Zaire: Mobutu and the military. Report no. cia-rdp83s00855r000100080001-6, Central Intelligence Agency. `https://www.cia.gov/library/readingroom/document/cia-rdp83s00855r000100080001-6` [accessed on 27.10.2020].

Ciccone, A. (2011). Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics 3*(4), 215–27.

CIESIN (2019). Gridded population of the world (gpw), v4. Dataset, Center for International Earth Science Information Network. `https://sedac.ciesin.columbia.edu/data/collection/gpw-v4` [accessed on 10.02.2019].

Cilliers, J., O. Dube, and B. Siddiqi (2016). Reconciling after civil conflict increases social capital but decreases individual well-being. *Science 352*(6287), 787–794.

CNA (2017). The role of water stress in instability and conflict. Final report CRM-2017-U-016532 of the CNA Military Advisory Board.

Collier, P. et al. (2003). *Breaking the conflict trap: Civil war and development policy*. World Bank Publications.

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

Collier, P., A. Hoeffler, and D. Rohner (2009). Beyond greed and grievance: feasibility and civil war. *Oxford Economic Papers 61*(1), 1–27.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics 92*(1), 1–45.

Cooley, S. S. and F. W. Landerer (2019). Gravity recovery and climate experiment (grace) follow-on (grace-fo) level-3 data product user handbook.

Corvalan, A. and M. Vargas (2015). Segregation and conflict: An empirical analysis. *Journal of Development Economics 116*, 212–222.

Couttenier, M., V. Petrencu, D. Rohner, and M. Thoenig (2019). The violent legacy of conflict: Evidence on asylum seekers, crime, and public policy in switzerland. *American Economic Review 109*(12), 4378–4425.

Couttenier, M. and R. Soubeyran (2014). Drought and civil war in sub-saharan africa. *The Economic Journal 124*(575), 201–244.

Cardenas, Juan Camilo, A. C.-C. and N. M. Mendez (2014). The hidden face of justice: fairness, discrimination and distribution in transitional justice processes. *Peace Economics, Peace Science and Public Policy 20*(1), 33–60.

Croicu, M. and R. Sundberg (2015). Ucdp georeferenced event dataset codebook version 4.0. *Journal of Peace Research 50*(4), 523–532.

Crost, B., J. Felter, and P. Johnston (2014). Aid under fire: Development projects and civil conflict. *American Economic Review 104*(6), 1833–56.

Crost, B., J. H. Felter, and P. B. Johnston (2016). Conditional cash transfers, civil conflict and insurgent influence: Experimental evidence from the philippines. *Journal of Development Economics 118*, 171–182.

Cunha, F. and J. Heckman (2007). The technology of skill formation. *American Economic Review 97*(2), 31–47.

Currie, J. and D. Almond (2011). Human capital development before age five. In D. Card and O. Ashenfelter (Eds.), *Handbook of Labor Economics*, Volume 4B, pp. 1315–1486. Elsevier.

Czaika, M. and K. Kis-Katos (2009). Civil conflict and displacement: village-level determinants of forced migration in aceh. *Journal of Peace Research 46*(3), 399–418.

Dal Bó, E., F. Finan, O. Folke, T. Persson, and J. Rickne (2017). Who becomes a politician? *The Quarterly Journal of Economics 132*(4), 1877–1914.

Daviet, B. et al. (2016). Revisiting the principle of education as a public good. Technical report, UNESCO. `http://www.unesco.org/new/en/education/themes/leading-the-international-agenda/rethinking-education/erf-papers/`, [accessed on 01.10.2019].

De Luca, G., R. Hodler, P. A. Raschky, and M. Valsecchi (2018a). Ethnic favoritism: An axiom of politics? *Journal of Development Economics 132*, 115–129.

De Luca, G., R. Hodler, P. A. Raschky, and M. Valsecchi (2018b). Ethnic favoritism: An axiom of politics? *Journal of Development Economics 132*, 115–129.

Deacon, R. T. (2009). Public good provision under dictatorship and democracy. *Public Choice 139*(1-2), 241–262.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic Literature 52*(3), 740–98.

Di Maio, M. and T. K. Nandi (2013). The effect of the israeli–palestinian conflict on child labor and school attendance in the west bank. *Journal of Development Economics 100*(1), 107–116.

Dickens, A. (2018). Ethnolinguistic favoritism in african politics. *American Economic Journal: Applied Economics 10*(3), 370–402.

Ding, Y., M. J. Hayes, and M. Widhalm (2011). Measuring economic impacts of drought: a review and discussion. *Disaster Prevention and Management: An International Journal*.

Do, Q.-A., K.-T. Nguyen, and A. N. Tran (2017). One mandarin benefits the whole clan: hometown favoritism in an authoritarian regime. *American Economic Journal: Applied Economics 9*(4), 1–29.

Do, Q.-T. and L. Iyer (2010). Geography, poverty and conflict in nepal. *Journal of Peace Research 47*(6), 735–748.

Döring, S. (2020). Come rain, or come wells: How access to groundwater affects communal violence. *Political Geography 76*, 102073.

Downs, A. (1957). An economic theory of political action in a democracy. *Journal of Political Economy 65*(2), 135–150.

Drazanova, L. (2019). Historical index of ethnic fractionalization dataset (hief). Dataset. Harvard Dataverse, version 2.

Dreher, A., A. Fuchs, R. Hodler, B. C. Parks, P. A. Raschky, and M. J. Tierney (2019). African leaders and the geography of china's foreign assistance. *Journal of Development Economics 140*, 44–71.

Dreher, A., A. Fuchs, A. Kammerlander, L. Kaplan, C. Robert, and K. Unfried (2020). The political leaders' affiliation database (plad). Dataset. Available at https://doi.org/10.7910/DVN/YUS575, Harvard Dataverse, V2.

Dube, O. and J. F. Vargas (2013). Commodity price shocks and civil conflict: Evidence from colombia. *The review of economic studies 80*(4), 1384–1421.

Eller, A., D. Abrams, and A. Gomez (2012). When the direct route is blocked: The extended contact pathway to improving intergroup relations. *International Journal of Intercultural Relations 36*(5), 637–646.

Esteban, J., L. Mayoral, and D. Ray (2012). Ethnicity and conflict: An empirical study. *American Economic Review 102*(4), 1310–42.

Esteban, J. and D. Ray (2011). Linking conflict to inequality and polarization. *American Economic Review 101*(4), 1345–74.

Fan, Y., H. Li, and G. Miguez-Macho (2013). Global patterns of groundwater table depth. *Science 339*(6122), 940–943.

Fazio, R. H. and M. A. Olson (2003). Implicit measures in social cognition research: Their meaning and use. *Annual Review of Psychology 54*(1), 297–327.

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

Fjelde, H. (2009). Buying peace? oil wealth, corruption and civil war, 1985—99. *Journal of Peace Research 46*(2), 199–218.

Flückiger, M. and M. Ludwig (2018). Youth bulges and civil conflict: causal evidence from sub-saharan africa. *Journal of Conflict Resolution 62*(9), 1932–1962.

Franck, R. and I. Rainer (2012). Does the leader's ethnicity matter? ethnic favoritism, education, and health in sub-saharan africa. *American Political Science Review 106*(2), 294–325.

GADM (2011). Gadm: database of global administrative areas. Technical report, University of California Berkely. `https://gadm.org/index.html`,[accessed on 18.06.2018].

GADM (2019). Gadm database of global administrative areas, version 3.6. Dataset, Global Administrative Areas. `www.gadm.org`. [accessed on 10.01.2019].

Garner, R., T. Naidu, C. Saavedra, P. Matamoros, and E. Lacroix (2012). Water management in mining: A selection of case studies. *International Council on Mining & Metals, London*.

Gates, S., H. Hegre, H. M. Nygård, and H. Strand (2012). Development consequences of armed conflict. *World Development 40*(9), 1713–1722.

Gilligan, M. J., E. N. Mvukiyehe, and C. Samii (2013). Reintegrating rebels into civilian life: Quasi-experimental evidence from burundi. *Journal of Conflict Resolution 57*(4), 598–626.

Girardin, L., P. Hunziker, L.-E. Cederman, N.-C. Bormann, and M. Vogt (2015). GROWup - Geographical Research On War, Unified Platform. https://growup.ethz.ch/about.

Girod, D. M. (2015). Reducing postconflict coup risk: The low windfall coup-proofing hypothesis. *Conflict Management and Peace Science 32*(2), 153–174.

Goemans, H. E., K. S. Gleditsch, and G. Chiozza (2009). Introducing archigos: A dataset of political leaders. *Journal of Peace Research 46*(2), 269–283.

Goldstone, J. A. (2008). Pathways to state failure. *Conflict Management and Peace Science 25*(4), 285–296.

Greenwald, A. G., B. A. Nosek, and M. R. Banaji (2003). Understanding and using the implicit association test: An improved scoring algorithm. *Journal of Personality and Social Psychology 85*(2), 197.

Guardian, T. (2004). Suharto, Marcos and Mobutu head corruption table. News report. `https://www.theguardian.com/world/2004/mar/26/indonesia.philippines` [accessed on 09.10.2020].

Habyarimana, J., M. Humphreys, D. N. Posner, and J. M. Weinstein (2007). Why does ethnic diversity undermine public goods provision? *American Political Science Review 101*(4), 709–725.

Hallberg, D. J. (2012). Prio conflict site 1989–2008: A geo-referenced dataset on armed conflict. *Conflict Management and Peace Science 29*(2), 219–232.

Han, Z., S. Huang, Q. Huang, G. Leng, H. Wang, Q. Bai, J. Zhao, L. Ma, L. Wang, and M. Du (2019). Propagation dynamics from meteorological to groundwater drought and their possible influence factors. *Journal of Hydrology 578*, 124102.

Harari, M. and E. L. Ferrara (2018). Conflict, climate, and cells: a disaggregated analysis. *Review of Economics and Statistics 100*(4), 594–608.

Harm, C. and M. J. Charap (1999). Institutionalized corruption and the kleptocratic state. In S. Gupta and G. Abed (Eds.), *Governance, Corruption, and Economic Performance*, Chapter 6. International Monetary Fund.

Hashim, A. (2003). Saddam husayn and civil-military relations in iraq: The quest for legitimacy and power. *The Middle East Journal*, 9–41.

Hegre, H. and H. M. Nygård (2015). Governance and conflict relapse. *Journal of Conflict Resolution 59*(6), 984–1016.

Hegre, H., H. Strand, S. Gates, and H. M. Nygard (2011). The conflict trap. In *Paper for the annual meeting of the American Political Science Association*.

Hendrix, C. S. (2010). Measuring state capacity: Theoretical and empirical implications for the study of civil conflict. *Journal of Peace Research 47*(3), 273–285.

Hendrix, C. S. and I. Salehyan (2012). Climate change, rainfall, and social conflict in africa. *Journal of Peace Research 49*(1), 35–50.

Hodler, R. and P. A. Raschky (2014a). Economic shocks and civil conflict at the regional level. *Economics Letters 124*(3), 530–533.

Hodler, R. and P. A. Raschky (2014b). Regional favoritism. *The Quarterly Journal of Economics 129*(2), 995–1033.

Homer-Dixon, T. F. (1994). Environmental scarcities and violent conflict: evidence from cases. *International Security 19*(1), 5–40.

Hsiang, S. M., M. Burke, and E. Miguel (2013). Quantifying the influence of climate on human conflict. *Science 341*(6151), 1235367.

Humphreys, M. and J. M. Weinstein (2007). Demobilization and reintegration. *Journal of Conflict Resolution 51*(4), 531–567.

ICF (2016). Demographic and health surveys (various) [datasets]. GPS data collection, ICF International [Distributor], Calverton, Maryland. `https://dhsprogram.com/What-We-Do/GPS-Data-Collection.cfm`, [accessed on 07.02.2018].

IDMC (2018). Global report on internal displaced, grid 2018. Technical report, Internal Displacement Monitoring Center (IDMC). Geneva.

Jakiela, P. and O. Ozier (2019). The impact of violence on individual risk preferences: evidence from a natural experiment. *Review of Economics and Statistics 101*(3), 547–559.

Justino, P. (2011). Violent conflict and human capital accumulation. IDS Working Papers 379, Brighton. Institute of Development Studies.

Kalnay, E., M. Kanamitsu, R. Kistler, W. Collins, D. Deaven, L. Gandin, M. Iredell, S. Saha, G. White, J. Woollen, et al. (1996). The ncep/ncar 40-year reanalysis project. *Bulletin of the American meteorological Society 77*(3), 437–472.

Kaplan, O. and E. Nussio (2018). Community counts: The social reintegration of ex-combatants in colombia. *Conflict Management and Peace Science 35*(2), 132–153.

Karpinski, A. and R. B. Steinman (2006). The single category implicit association test as a measure of implicit social cognition. *Journal of Personality and Social Psychology 91*(1), 16.

Kesternich, I., B. Siflinger, J. P. Smith, and J. K. Winter (2014). The effects of world war ii on economic and health outcomes across europe. *Review of Economics and Statistics 96*(1), 103–118.

Klosko, S., D. Rowlands, S. Luthcke, F. Lemoine, D. Chinn, and M. Rodell (2009). Evaluation and validation of mascon recovery using grace kbrr data with independent mass flux estimates in the mississippi basin. *Journal of Geodesy 83*(9), 817–827.

Knight, M. and A. Özerdem (2004). Guns, camps and cash: Disarmament, demobilization and reinsertion of former combatants in transitions from war to peace. *Journal of Peace Research 41*(4), 499–516.

Kondylis, F. (2010). Conflict displacement and labor market outcomes in post-war bosnia and herzegovina. *Journal of Development Economics 93*(2), 235–248.

Kramon, E. and D. N. Posner (2013). Who benefits from distributive politics? how the outcome one studies affects the answer one gets. *Perspectives on Politics 11*(2), 461–474.

Kramon, E. and D. N. Posner (2016). Ethnic favoritism in education in kenya. *Quarterly Journal of Political Science 11*(1), 1–58.

La Mattina, G. (2017). Civil conflict, domestic violence and intra-household bargaining in post-genocide rwanda. *Journal of Development Economics 124*, 168–198.

La Mattina, G. (2018). How persistent is the effect of conflict on primary education? lon-run evidence from the rwandan genocide. *Economics Letters 163*, 32–35.

Lai, B. and C. Thyne (2007). The effect of civil war on education, 1980—97. *Journal of Peace Research 44*(3), 277–292.

Landerer, F., F. Flechtner, H. Save, F. Webb, T. Bandikova, W. Bertiger, S. Bettadpur, S. Byun, C. Dahle, H. Dobslaw, et al. (2020). Extending the global mass change data record: Grace follow-on instrument and science data performance. *Geophysical Research Letters 47*, e2020GL088306.

Lee, C. (2014). In utero exposure to the korean war and its long-term effects on socioeconomic and health outcomes. *Journal of Health Economics 33*, 76–93.

Lei, Y.-H. and G. Michaels (2014). Do giant oilfield discoveries fuel internal armed conflicts? *Journal of Development Economics 110*, 139–157.

León, G. (2012). Civil conflict and human capital accumulation the long-term effects of political violence in perú. *Journal of Human Resources 47*(4), 991–1022.

Lezhnev, S. (2016). A criminal state, understanding and countering institutionalized corruption and violence in the democratic republic of the congo. Violent kleptocracy series: East and central africa, Enough. `https://enoughproject.org/reports/` [accessed on 27.10.2020].

Malhotra, D. and S. Liyanage (2005). Long-term effects of peace workshops in protracted conflicts. *Journal of Conflict Resolution 49*(6), 908–924.

Malovany, P. (2017). *Wars of Modern Babylon: A History of the Iraqi Army from 1921 to 2003*. University Press of Kentucky.

Malthus, T. R. (1798). An essay on the principle of population as it affects the future improvement of society, with remarks on the speculations of mr godwin, m. *Condorcet, and other writers. London: J. Johnson*.

Marshall, M. G., T. R. Gurr, and K. Jaggers (2019). Polity iv project, dataset user's manual. Technical report, Center for Systemic Peace (CSP). Vienna, VA.

Maus, V., S. Giljum, J. Gutschlhofer, D. M. da Silva, M. Probst, S. L. Gass, S. Luckeneder, M. Lieber, and I. McCallum (2020). A global-scale data set of mining areas. *Scientific Data 7*(1), 1–13.

McDougall, A. (2009). State power and its implications for civil war colombia. *Studies in Conflict & Terrorism 32*(4), 322–345.

McKee, T. B., N. J. Doesken, and J. Kleist (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology 17*(22), 179–183.

Michalopoulos, S. and E. Papaioannou (2013). Pre-colonial ethnic institutions and contemporary african development. *Econometrica 81*(1), 113–152.

Miguel, E. and G. Roland (2011). The long-run impact of bombing vietnam. *Journal of Development Economics 96*(1), 1–15.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy 112*(4), 725–753.

Milrad, S. (2017). *Synoptic Analysis and Forecasting: An Introductory Toolkit*. Elsevier.

Minoiu, C. and O. Shemyakina (2012). Child health and conflict in côte d'ivoire. *American Economic Review 102*(3), 294–99.

Minoiu, C. and O. N. Shemyakina (2014). Armed conflict, household victimization, and child health in côte d'ivoire. *Journal of Development Economics 108*, 237–255.

Montalvo, J. G. and M. Reynal-Querol (2005). Ethnic diversity and economic development. *Journal of Development Economics 76*(2), 293–323.

Monteiro, J. and R. Rocha (2017). Drug battles and school achievement: evidence from rio de janeiro's favelas. *Review of Economics and Statistics 99*(2), 213–228.

Nadler, A. (2012). Intergroup reconciliation: Definitions, processes, and future directions. In L. R. Tropp (Ed.), *The Oxford handbook of Intergroup Conflict*, pp. 291–309. Oxford University Press.

Natural Earth (2020). River and lake centerlines. Dataset, Natural Earth. available at `https://www.naturalearthdata.com/downloads/10m-physical-vectors/10m-rivers-lake-centerlines/`, [accessed on 30.9.2020].

Nelson, T. (2010). When disaster strikes: on the relationship between natural disaster and interstate conflict. *Global Change, Peace & Security 22*(2), 155–174.

New York Times (2003). In Iraq's tribes, US faces a formidable wild card. News report. `https://www.nytimes.com/2003/01/05/world/threats-responses-allegiances-iraq-s-tribes-us-faces-formidable-wild/card.html` [accessed on 05.10.2020].

NOAA (2019). Version 4 dmsp-ols nighttime lights time series. Webpage, National Oceanic and Atmospheric Administration. `https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html`, [accessed on 21.9.2019].

Nunn, N. and N. Qian (2014). Us food aid and civil conflict. *American Economic Review 104*(6), 1630–66.

Osborne, M., B. D'Exelle, and A. Verschoor (2018). Truly reconciled? a dyadic analysis of post-conflict social reintegration in northern uganda. *Journal of Peace Research 55*(1), 107–121.

Østby, G., R. Nordås, and J. K. Rød (2009). Regional inequalities and civil conflict in sub-saharan africa. *International Studies Quarterly 53*(2), 301–324.

Østby, G. and H. Urdal (2011). Education and civil conflict: A review of the quantitative, empirical literature. *Background paper prepared for the Education for All Global Monitoring Report*.

Otto, B. and L. Schleifer (2020). Domestic water use grew over 600 percent over the past 50 years. Webpage, World Resource Institute. `https://www.wri.org/blog/2020/02/growth-domestic-water-use`, [accessed 16.07.2020].

O'Loughlin, J., F. D. Witmer, A. M. Linke, A. Laing, A. Gettelman, and J. Dudhia (2012). Climate variability and conflict risk in east africa, 1990–2009. *Proceedings of the National Academy of Sciences 109*(45), 18344–18349.

Paluck, E. L. (2009). Reducing inter-group prejudice and conflict using the media: A field experiment in rwanda. *Journal of Personality and Social Psychology 96*(3), 574–587.

Paolini, S., J. Harwood, and M. Rubin (2010). Negative intergroup contact makes group memberships salient: Explaining why intergroup conflict endures. *Personality and Social Psychology Bulletin 36*(12), 1723–1738.

Paolini, S., J. Harwood, M. Rubin, S. Husnu, N. Joyce, and M. Hewstone (2014). Positive and extensive intergroup contact in the past buffers against the disproportionate impact of negative contact in the present. *European Journal of Social Psychology 44*(6), 548–562.

Paulus, A. and M. Vashakmadze (2009). Asymmetrical war and the notion of armed conflict-a tentative conceptualization. *International Review of the Red Cross 91*, 95.

Pettersson, T. and M. Öberg (2020). Organized violence, 1989–2019. *Journal of Peace Research 57*(4), 597–613.

Pettigrew, T. F. and L. R. Tropp (2006). A meta-analytic test of intergroup contact theory. *Journal of Personality and Social Psychology 90*(5), 751–783.

Pilster, U. and T. Böhmelt (2011). Coup-proofing and military effectiveness in interstate wars, 1967–99. *Conflict Management and Peace Science 28*(4), 331–350.

Powell, J. (2019). Leader survival strategies and the onset of civil conflict: A coup-proofing paradox. *Armed Forces & Society 45*(1), 27–44.

Quinlivan, J. T. (1999). Coup-proofing: Its practice and consequences in the middle east. *International Security 24*(2), 131–165.

Richards, A. and N. Singh (2002). Inter-state water disputes in india: Institutions and policies. *International Journal of Water Resources Development 18*(4), 611–625.

Richts, A., W. Struckmeier, and M. Zaepke (2011). Whymap and the groundwater resources of the world 1: 25,000,000 sustaining groundwater resources, international year of planet earth ed j jones.

Rydell, R. J. and A. R. McConnell (2006). Understanding implicit and explicit attitude change: a systems of reasoning analysis. *Journal of Personality and Social Psychology 91*(6), 995.

Salehyan, I., C. S. Hendrix, J. Hamner, C. Case, C. Linebarger, E. Stull, and J. Williams (2012). Social conflict in africa: A new database. *International Interactions 38*(4), 503–511.

Sánchez, G. et al. (2013). ¡basta ya! colombia: memorias de guerra y dignidad. Informe general del grupo de memoría y histrória, Centro de Memorría Histrórica.

Sarsons, H. (2015). Rainfall and conflict: A cautionary tale. *Journal of Development Economics 115*, 62–72.

Scacco, A. and S. S. Warren (2018). Can social contact reduce prejudice and discrimination? evidence from a field experiment in nigeria. *American Political Science Review 112*(3), 654–677.

Scanlon, B. R., Z. Zhang, H. Save, D. N. Wiese, F. W. Landerer, D. Long, L. Longuevergne, and J. Chen (2016). Global evaluation of new grace mascon products for hydrologic applications. *Water Resources Research 52*(12), 9412–9429.

Scartascini, C., C. Cruz, and P. Keefer (2018). The database of political institutions 2017 (dpi2017). *Washington, Banco Interamericano de Desarrollo*.

Scheffran, J., M. Brzoska, J. Kominek, P. Link, J. Schilling, et al. (2012). Climate change and violent conflict. *Science 336*(6083), 869–871.

Schulz, K. J. and J. A. Briskey (2005). Major mineral deposits of the world. Technical report, US Geological Survey.

SEDAC (2011). Global rural-urban mapping project, version 1 (grumpv1): Urban extents grid. Dataset, NASA Socioeconomic Data and Applications Center (SEDAC), Center for International Earth Science Information Network (CIESIN), International Food Policy Research Institute (IFPRI), The World Bank, and Centro Internacional de Agricultura Tropical (CIAT). available at `https://sedac.ciesin.columbia.edu/data/set/grump-v1-urban-extents`, [accessed on 15.10.2020].

Shemyakina, O. (2011). The effect of armed conflict on accumulation of schooling: Results from tajikistan. *Journal of Development Economics 95*(2), 186–200.

Siebert, S., V. Henrich, K. Frenken, and J. Burke (2013). Update of the digital global map of irrigation areas to version 5. *Rheinische Friedrich-Wilhelms-Universität, Bonn, Germany and Food and Agriculture Organization of the United Nations, Rome, Italy*.

Singhal, S. (2019). Early life shocks and mental health: The long-term effect of war in vietnam. *Journal of Development Economics 141*, 102244.

Slettebak, R. T. (2012). Don't blame the weather! climate-related natural disasters and civil conflict. *Journal of Peace Research 49*(1), 163–176.

Sommers, M. (2002). Children, education and war: Reaching education for all (efa): Objectives in countries affected by conflict. Conflict Prevention and Reconstruction Unit Working Paper 1, The World Bank, Washington D.C.

Spagat, M., A. Mack, T. Cooper, and J. Kreutz (2009). Estimating war deaths: An arena of contestation. *Journal of Conflict Resolution 53*(6), 934–950.

Stina, H. (2019). Ucdp ged, codebook version 19.1. *Department of Peace and Conflict Research, Uppsala University*.

Stoet, G. (2017). Psytoolkit: A novel web-based method for running online questionnaires and reaction-time experiments. *Teaching of Psychology 44*(1), 24–31.

Strand, H., S. A. Rustad, H. Urdal, and H. M. Nygård (2019). Trends in armed conflict, 1946–2018. Report on conflict trends, Peace research institute Oslo (PRIO).

Sudduth, J. K. (2017). Coup risk, coup-proofing and leader survival. *Journal of Peace Research 54*(1), 3–15.

Sundberg, R. and E. Melander (2013). Introducing the ucdp georeferenced event dataset. *Journal of Peace Research 50*(4), 523–532.

Tajfel, H. and J. Turner (1986). The social identity theory of intergroup behavior. *Psychology of Intergroup Relations*, 7–24.

Tellez, J. F. (2019). Worlds apart: Conflict exposure and preferences for peace. *Journal of Conflict Resolution 63*(4), 1053–1076.

Theisen, O. M., N. P. Gleditsch, and H. Buhaug (2013). Is climate change a driver of armed conflict? *Climatic change 117*(3), 613–625.

Thenkabail, P. S., C. M. Biradar, P. Noojipady, V. Dheeravath, Y. Li, M. Velpuri, M. Gumma, O. R. P. Gangalakunta, H. Turral, X. Cai, et al. (2009). Global irrigated area map (giam), derived from remote sensing, for the end of the last millennium. *International Journal of Remote Sensing 30*(14), 3679–3733.

Thyne, C. L. and J. M. Powell (2016). Coup d'état or coup d'autocracy? how coups impact democratization, 1950–2008. *Foreign policy analysis 12*(2), 192–213.

Tollefsen, A. F., H. Strand, and H. Buhaug (2012). Prio-grid: A unified spatial data structure. *Journal of Peace Research 49*(2), 363–374.

Turner, R. N., R. J. Crisp, and E. Lambert (2010). Imagining intergroup contact can improve intergroup attitudes. *Group Processes and Intergroup Relations 10*(4), 427–441.

UNESCO (2017). Reducing global poverty through universal primary and secondary education: Efa global monitoring report 2017. UNESCO Policy Paper 32, Fact sheet 44, United Nations Educational, Scientific and Cultural Organization Institute for Statistics, Montreal, Canada.

UNICEF (2017). 25 million children out of school in conflict zones - unicef. Technical report, United Nations International Children's Emergency Fund. `https://www.unicef.org/media/media_95861.html`, [accessed on 05.02.2018].

Unidadvictimas (2017). Decret of ley number 899. Technical report, Precidency of the Colombian Republic. `https://www.unidadvictimas.gov.co/es/decreto-899-del-29-de-mayo-de-2017/37041`, [accessed on 07.01.2020].

UNRIC (2018). The guerrilla groups in colombia. Technical report, United Nations Regional Information Center for Western Europe (UNRIC). `https://www.unric.org/en/colombia/27013-the-guerrilla-groups-in-colombia`, [accessed on 30.11.2018].

Valente, C. (2014). Education and civil conflict in nepal. *The World Bank Economic Review 28*(2), 354–383.

Valente, C. (2015). Civil conflict, gender-specific fetal loss, and selection: A new test of the trivers–willard hypothesis. *Journal of Health Economics 39*, 31–50.

Valero, L. P. V. (2018). Agencia para la reincorporación y normalización (arn) exalta el trabajo del sena con los desmovilizados. Technical report, National Training Service (SENA). `http://www.sena.edu.co/es-co/Noticias/Paginas/noticia.aspx?IdNoticia=3382`, [accessed on 07.01.2020].

Vicente-Serrano, S. M., S. Beguería, and J. I. López-Moreno (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of Climate 23*(7), 1696–1718.

Voci, A. and M. Hewstone (2003). Intergroup contact and prejudice toward immigrants in italy: The mediational role of anxiety and the moderational role of group salience. *Group Processes and Intergroup Relations 6*(1), 37–54.

Vogt, M., N.-C. Bormann, S. Rüegger, L.-E. Cederman, P. Hunziker, and L. Girardin (2015, October). Integrating Data on Ethnicity, Geography, and Conflict: The Ethnic Power Relations Data Set Family. *Journal of Conflict Resolution 59*(7), 1327–1342.

Voors, M. J., E. E. Nillesen, P. Verwimp, E. H. Bulte, R. Lensink, and D. P. Van Soest (2012). Violent conflict and behavior: a field experiment in burundi. *American Economic Review 102*(2), 941–64.

Waliser, D. and B. Guan (2017). Extreme winds and precipitation during landfall of atmospheric rivers. *Nature Geoscience 10*(3), 179–183.

Watkins, M. M., D. N. Wiese, D.-N. Yuan, C. Boening, and F. W. Landerer (2015). Improved methods for observing earth's time variable mass distribution with grace using spherical cap mascons. *Journal of Geophysical Research: Solid Earth 120*(4), 2648–2671.

Weidmann, N. B., J. K. Rød, and L.-E. Cederman (2010). Representing ethnic groups in space: A new dataset. *Journal of Peace Research 47*(4), 491–499.

Wiese, D. N., F. W. Landerer, and M. M. Watkins (2016). Quantifying and reducing leakage errors in the jpl rl05m grace mascon solution. *Water Resources Research 52*(9), 7490–7502.

Wiese, D. N., D.-N. Yuan, C. Boening, F. W. Landerer, and M. M. Watkins (2018). Jpl grace mascon ocean, ice, and hydrology equivalent water height release 06 coastal resolution improvement (cri) filtered version 1.0. ver. 1.0. Technical report, Physical Oceanography Distributed Active Archive Center (PO:DAAC), CA, USA. `http://dx.doi.org/10.5067/TEMSC-3MJC6.`

Wig, T. and A. F. Tollefsen (2016). Local institutional quality and conflict violence in africa. *Political Geography 53*, 30–42.

World Bank Group (2018). *Pathways for peace: Inclusive approaches to preventing violent conflict*. World Bank.

World Economic Forum (2020). Water scarcity is one of the greatest challenges of our time. Webpage, World Economic Forum. `https://www.weforum.org/agenda/2019/03/water-scarcity-one-of-the-greatest-challenges-of-our-time`, [accessed on 24.02.2020].

WorldBank (2016). World development indicators (wdi). Technical report, World Bank Washington, DC.

Worldbank (2020). Education statistics: Country at a glance - colombia. Technical report, The World Bank.

Wright, Donlad W.and Reese, T. R. (2008). On point ii: Transition to a new campaign. News report, US Army Combined Arms Center. `https://www.globalsecurity.org/military/library/report/2008/onpoint/chap11-01.htm` [accessed on 27.10.2020].

Wrong, M. (2000). The emperor mobutu. *Transition 9*(1), 92–112.

Wucherpfennig, J., N. W. Metternich, L.-E. Cederman, and K. S. Gleditsch (2012). Ethnicity, the state, and the duration of civil war. *World Politics 64*, 79.

Yanagizawa-Drott, D. (2014). Propaganda and conflict: Evidence from the rwandan genocide. *The Quarterly Journal of Economics 129*(4), 1947–1994.

Young, C. and T. E. Turner (1985). *The Rise and Decline of the Zairian State*. University of Wisconsin Press.

Appendix A

Appendix for chapter 3

A.1 Further robustness checks

TABLE A.1: Political favoritism and conflict

	IHS(casualties)		
	(1)	(2)	(3)
Leader region$_{t-1}$	-0.003	-0.001	-0.023
	(0.004)	(0.003)	(0.017)
Observations	1,177,805	1,177,805	1,177,805
R-squared	0.364	0.264	0.387

Note: The table reports OLS regression estimates of regressing the conflict outcome variables on an indicator of the birth region of the effective leader. Regressions include country-year and region fixed effects as well as standard controls. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A.2: Political favoritism and conflict at the first administrative level

	IHS(casualties)	
	(1)	(2)
Leader autoc$_{t-1}$	-0.132	-0.127
	(0.331)	(0.330)
Leader non-autoc$_{t-1}$	0.121	0.118
	(0.124)	(0.123)
Observations	75,539	75,539
R-squared	0.605	0.606

Note: The table reports OLS regression estimates of regressing the inverse hyperbolic sine of the number of casualties on dummies of (non-)autocratic leader regions at the first administrative level. Regressions include country-year fixed effects, standard controls and region fixed effects, whereas region refers here to the 1st admin level. Standard errors are clustered at the country level. *** p<0.01, ** p<0.05, * p<0.1.

TABLE A.3: Heterogeneous effects by irregular entry and political regime switcher

	IHS(casualties)	
	(1)	(2)
Leader autoc$_{t-1}$	-0.118**	-0.085*
	(0.054)	(0.050)
Leader non-autoc$_{t-1}$	-0.023	-0.009
	(0.019)	(0.019)
Leader autoc$_{t-1}$ x switcher	0.046	
	(0.045)	
Leader non-autoc$_{t-1}$ x switcher	0.073*	
	(0.040)	
Leader autoc$_{t-1}$ x irregular entry		-0.027
		(0.087)
Leader non-autoc$_{t-1}$ x irregular entry		0.050
		(0.072)
Observations	1,177,805	1,177,805
R-squared	0.387	0.387

Note: The table reports OLS regression estimates of regressing the inverse hyperbolic sine of the number of casualties on dummies of (non-)autocratic leader regions and their interaction terms with indicators of political regime switchers and leaders' irregular entries into office. Regressions include country-year and region fixed effects as well as standard controls. Standard errors are clustered at the country level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

A.2 Data appendix

Our analysis combines geo-coded conflict event data with information on the birth places of political leaders. The unit of observation is region-year, whereby region refers to the second administrative level of a country provided by the GADM dataset v3.6 (GADM, 2019). Using the information of leaders' birth places we define a region as a leader region if the national leader was born in the respective region. Our final sample is an unbalanced panel dataset with 44,025 regions in 2,963 provinces and 172 countries over the years 1989 – 2015 resulting in a total of 1,177,805 observations. We define and describe all variables that are used in the empirical analysis in the following.

Conflict data

The dependent variables in our empirical analysis are different measures of conflict, which are taken from the UCDP Georeferenced Event Dataset (GED) global version 19.1 provided by the UCDP (Sundberg and Melander, 2013; Stina, 2019). It reports violent events for the years 1989 until 2018 and entails information on the exact location and timing of the event as well as the estimated number of casualties. The UCDP GED conflict event dataset is one of the most accurate data sets on global conflicts available. We exclude all conflict events with imprecise geo-coded information, that is, conflicts for which the geo-precision is less accurate than at the second administrative level.

We measure conflict in three ways. First, we construct a dummy variable that equals one if there occurred at least one conflict in a given region and year. Second, we readjust the conflict dummy according to the number of battle-related deaths by setting the conflict variables only to one if the sum of all conflict-related fatalities in a region and year is larger than 500. Third, in order to see changes in the intensity of conflict, we use the inverse hyperbolic sine function of the number of battle-related deaths per region and year.

In an extension of our baseline regressions, we further divide our conflict variables by their actors, following the definition of the UCDP GED database, into state-based conflict events, non-state-based conflicts and one-sided violence. According to the UCDP definition, a conflict is characterized as state-based if a government of a state is active in the conflict, whereas non-state based conflict refers to violence between two non-governmental organized actors. One-sided violence includes attacks against civilians of any organized actor (Sundberg and Melander, 2013). We readjust the third category by eliminating the attacks against civilians from non-governmental actors. According to these definitions, we define a year to be a state-based conflict year if at least one state-based conflict event in the respective region and year has occurred and use the inverse hyperbolic sine function of the number of fatalities in these events. The same procedure applies to the other two categories.

Data on political leaders

To identify political leaders around the globe, we rely on the Archigos database v. 4.1 (Goemans et al., 2009). Archigos lists the effective national political leaders in 188 countries during the years 1875 to 2015 and provides further information on their time in office, type of entry (if the leader came into office regularly or via a coup) and exit.

We complement the database with the leaders' geo-referenced birth places from the PLAD dataset from Dreher et al. (2020) and identify the corresponding regions on the second administrative level. Out of this, we construct *Leader region*, which is an indicator variable equal to one if a region is the birth region of the national leader and 0 otherwise. For a graphical representation of the leader regions, see figure 3.1.

Ethnicity

In order to investigate the effects of ethnic favoritism on conflict, we use the ethnic affiliation of national leaders provided by the PLAD dataset. We implement two approaches. The first approach is a straightforward replacement of the second administrative regions with ethnic homelands from the GeoEPR2019 dataset (Vogt et al., 2015). Using this dataset, we identify the ethnic home regions of the ethnicities of the politicians. Thus we identify the leader region identically to the approach with the GADM regions. In the second approach, we change the level of observations from regions to actors (ethnicities). The Geographical Research On War, Unified Platform (Growup) database (Girardin et al., 2015) attributes ethnicities to conflict actors irrespective of where the conflict takes place. Combined with the ethnic affiliation of national leaders, we can identify which ethnic conflict groups belong to the same ethnicity than the leader in autocracies and non-autocratic regimes (*Ethnic leader autoc* and *Ethnic leader non-autoc*).

In the channel analysis, we use the Historical Index of Ethnic Fractionalization (HIEF) from Drazanova (2019) to divide countries by their ethnic fractionalization along the median. The measure is an index that classifies countries based on their ethnic fractionalization. It theoretically ranges from 0 (every individual belongs to the same ethnic group) to 1 (every individual represents an individual group).

Political regime

We classify countries into autocratic and non-autocratic based on the Database of Political Institutions (DPI2017) (Scartascini et al., 2018). A political regime is defined as autocratic if there are no consolidated democratic institutions and the leadership is personality-based. More specifically, the DPI defines a country as autocratic if it either has no legislature, an unelected legislature, an elected legislature but only one candidate or party, or if there are multiple parties but only one party won seats.

The main variables of interest are *Leader autoc* and *Leader non-autoc*. Both are dummy variables that are equal to one if a) the region is the home region of the national leader and b) the country is an autocracy in case of *Leader autoc* or not an autocracy respectively for *Leader non-autoc*. In our sample, 20 countries are classified as autocratic throughout the whole sample period, 69 as non-autocratic and 83 countries changed the political system during the period. Of the 44,025 regions in our sample, 632 regions are birth regions of any political leader, 204 regions are birth regions of an autocratic leader and 533 regions are birth regions of a non-autocratic leader.

Weather shocks

In order to account for local economic shocks, we include indicators for drought and abundant rain from the Global SPEI database (version 2.5). The database provides standardized precipitation-evapotranspiration indexes (SPEI) for the years 1901 – 2015 on a monthly basis and 0.5 degree spatial grid resolution (Vicente-Serrano et al., 2010). It measures precipitation anomalies by a standardized z-score that is constructed out of monthly precipitation data minus the potential estimated evapotranspiration. Thus, it extends the popular Standardized Precipitation Index (SPI) by also taking surface evaporation and plant transpiration resulting from higher temperatures into account (Vicente-Serrano et al., 2010). Based on the SPEI index measured at 3-month scale, we define a month to be very dry if the SPEI index is equal or below –1 and very wet if the value is equal or above 1. As a measure for local economic shocks, $flood$ reports the number of very wet months in a year (or very dry months for $drought$, respectively) that a region experienced.

Population density

Regions with a high number of citizens have mechanically a higher likelihood to provide the political leader. At the same time, population size has been shown to be a determinant of conflict incidence (Brückner, 2010). To take this potential confounding factor into account, we control for the logarithm of yearly population size in a region. Using data from GPWv4 (Gridded Population of the World) dataset (CIESIN, 2019), we calculate the average population density for every region. Since the data is only available on a 5-year basis, we use a linear interpolation for the missing years.

Regional economic development

For a measure of regional economic development and to investigate the *'welfare channel'*, we make use of the nighttime-light data provided by the NOAA's national geographic data center of the earth observatory group. We use the Version 4 DMSP-OLS Nighttime Lights Time Series (NOAA, 2019) that provides average yearly visible stable lights at cloud free coverage on 30 arc second grids for the years 1992 to 2013.[1]

[1] As the Nighttime Lights Time Series is available for the years 1992 – 2013, our sample is restricted to these years in the 'welfare channel' analysis.

We aggregate the data on the second administrative level of a country by taking the area-sized weighted average.

Following Michalopoulos and Papaioannou (2013), we use the logarithm of nighttime lights plus 0.01. Nighttime light data are a good proxy for regional economic development and especially helpful in developing countries, where precise information on a geographical fine scale are rare (Bruederle and Hodler, 2018). Using nighttime light data as a proxy for economic development mediating the relation between political favoritism and conflict, we can investigate whether the effect of political favoritism on economic development translates into changes in conflict.

Natural ressources

We use the PRIO-GRID database (version 2.0) (Tollefsen et al., 2012) to identify regions with oil or gas deposits and to account for population growth. World-market oil and gas prices stem from the World Bank.

Natural resources such as oil are another important economic factor on the local level that potentially confound the relation between leader region and conflict. We interact the world-market price of oil and gas with indicator variables that determine whether oil or gas deposits are present in a region to control for these kinds of economic shocks. As an robustness check we control for further natural resources in the same way. Therefore, we use the information from Berman et al. (2017). We also use this data in the channel analysis.

Afrobarometer

To investigate the *'in-group favoritism channel'* and the *'coup-proofing channel'* we use information of citizens' perceptions and attitudes towards political institutions in African countries provided by Afrobarometer (2019). The Afrobarometer is a repeated survey on public and political attitudes that provides geo-localized data in 37 African countries over the years 1999 to 2019. We use the survey rounds 1 to 6 and aggregate perceptions and attitudes on the second administrative level of the country by taking the average values. Our sample is thereby reduced to around 7,000 region-year observations from 35 African countries.[2]

Enumerators of the surveys are asked to state whether they have seen a soldier or army vehicle, policemen, police vehicle or station on the way to the survey location. We use these statements as indicators of the amount of security protection. All answers are aggregated on the region level, taking the weighted average. We investigate the statements separately as well as in a combined index, named *state force*.

Changes in attitudes and behavior of citizens are analysed using the rating of trust in the political leader, the approval of his/her performance and their reported political

[2] For certain outcome variables (corruption leader, trust leader and performance leader), we lose 1-2 countries, as the question is not asked in these countries.

engagement. Additionally, participants in the surveys were asked about their perception of the extent of corruption in the police and leader office on a 4 point Liker scale, which we take as an indicator of the level of corruption in the respective region.

A detailed description of the variables used can be found in the table A.6 in the appendix, and table 6.1 provides the descriptive statistics of the main variables.

TABLE A.4: List of countries in the main sample

Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Côte d'Ivoire, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Luxembourg, Macedonia, Madagascar, Malawi, Malaysia, Mali, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Korea, Northern Cyprus, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Republic of Congo, Romania, Russia, Rwanda, Samoa, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovakia, Slovenia, Solomon Islands, Somalia, South Africa, South Korea, South Sudan, Spain, Sri Lanka, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syria, Taiwan, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe

TABLE A.5: List of countries and years of the Afrobarometer sample

Country	**Years**
Algeria	2013, 2015
Angloa	2006, 2008, 2012
Benin	2005, 2008, 2011, 2014
Botswana	1999, 2003, 2005, 2008, 2012, 2014
Burkina Faso	2008, 2012, 2015
Burundi	2012, 2014
Cameroon	2013, 2015
Cape Verde	2002, 2005, 2008, 2011, 2014
Ivory Coast	2013, 2014
Egypt	2013, 2015
Ghana	2002, 2005, 2008, 2012, 2014
Guinea	2013, 2015
Kenya	2003, 2005, 2008, 2011, 2014
Lesotho	2000, 2003, 2005, 2008, 2012, 2014
Liberia	2008, 2012, 2015
Madagascar	2005, 2008, 2013, 2014, 2015
Malawi	1999, 2003, 2005, 2008, 2012, 2014
Mali	2001, 2002, 2005, 2008, 2012, 2013, 2014
Mauritius	2012, 2014
Morocco	2013, 2015
Mozambique	2002, 2005, 2008, 2012, 2015
Namibia	2003, 2006, 2008, 2012, 2014
Niger	2013, 2015
Nigeria	2003, 2005, 2008, 2012, 2013, 2014, 2015
Senegal	2002, 2005, 2008, 2013, 2014
Sierra Leone	2012, 2015
South Africa	2000 2002 2006 2008 2011 2015
Sudan	2013, 2015
Tanzania	2001, 2003, 2005, 2008, 2012, 2014
Togo	2012, 2014
Tunisia	2013, 2015
Uganda	2002, 2005, 2008, 2011, 2012, 2015
Zambia	1999, 2003, 2005, 2009, 2012, 2013, 2014
Zimbabwe	1999, 2004, 2005, 2009, 2012, 2014

TABLE A.6: Definitions of variables

Variable name	Description	Source
	Regional favoritism	
Any conflict	Dummy variable for whether a region experienced at least one conflict event in a given year and region	UCDP GED
Conflict (death $\geq$ 25)	Dummy variable for whether a region experienced at least one conflict event resulting in 25 deaths or multiple conflict events summing up to 25 deaths in a given year	UCDP GED
IHS(casualties)	Inverse hyperbolic sine function of the number of battle-related casualties a region experiences in a given year	UCDP GED
Leader region	Dummy variable indicating if the national leader was born in this region	PLAD
Autocratic regime	Indicator variable for whether a region is in an autocratic regime at time t. Autocratic regime is defined in the World Bank Database of political institutions as a system with no consolidated democratic institutions and a leadership that is personality-based.	WDPI
Leader (non-)autoc	Based on the autocratic regime definition, we differentiate between autocratic and non-autocratic countries. Leader autoc refers to leader regions in autocratic countries and leader non-autoc respectively to leader regions in non-autocratic countries.	Archigos, PLAD, GADM, WDPI
Flood	Number of wet months (defined as the z-score of SPEI being larger than 1) in a given year and region	SPEIbase
Drought	Number of dry months (defined as the z-score of SPEI being larger than 1) in a given year and region	SPEIbase
Ln(Population)	Logarithm of population density	NOAA
Oil x ln(price$_{oil}$)	Interaction of dummy that a region has oil reserves and the world-market price of oil.	World Bank, Prio-Grid
Gas x ln(price$_{gas}$)	Interaction of dummy that a region has gas reserves and the world-market price of gas.	World Bank, Prio-Grid
	Ethnic favoritism	
Ethnic homelands	Region that is classified as ethnic homeland by the EPR dataset	GeoEPR
Ethnicity	We use the ACD2EPR dataset to connect conflict actors to ethnic groups. A non-state-based conflict actor is connected to a certain ethnic group if the actor recruits persons from this ethnic group and states to act on behalf of the ethnicity.	ACD2EPR
Ethnic leader (non-) autoc	Dummy variable indicating the ethnic homeland or ethnicity that the current leader belongs to. Ethnic homeland and ethnicity as defined above.	PLAD
	Channel analysis	
IHS(state casualties)	Inverse hyperbolic sine function of battle-related deaths of state-based conflicts in a year and region. A conflict is a state-based conflict according to UCDP GED classification.	UCDP GED
IHS(non-state casualties)	Inverse hyperbolic sine function of battle-related deaths of non-state-based conflicts in a year and region. A conflict is a non-state-based conflict according to UCDP GED classification.	UCDP GED
IHS(civilians casualties)	Inverse hyperbolic sine function of battle-related deaths of conflicts against civilians by governmental actors in a year and region. A conflict is classified as violence against civilians according to UCDP GED classification.	UCDP GED

Variable name	Description	Source
Nighttime lights	Logarithm of nighttime lights + 0.01	NOAA
Army	Share of responses of enumerators that have seen any soldier or army vehicles on their way to interview per region and year	Afrobarometer
Police	Share of responses of enumerators that have seen any policemen, police station or police vehicles on their way to interview per region and year	Afrobarometer
State force	Share of responses of enumerators that have seen either army or police presence on way to interview per region and year	Afrobarometer
Trust leader	Average trust level towards political leader measured on a Likert scale from 0 to 3 per region and year	Afrobarometer
Performance leader	Average approval of the performance from national leader, measured on Likert scale from 1 to 4 per region and year	Afrobarometer
Activism	Average level of "using violence for political cause or going to demonstrations" from survey respondents in a region and year; Likert scale from 0 (never would do) to 4 (yes, often)	Afrobarometer
Corruption index	Index combining corruption leader and corruption police.	Afrobarometer
Political corruption	Average perceived level of corruption among president and officials in office per region and year; Likert scale from 0 (never would do) to 4 (yes, often)	Afrobarometer
Police corruption	Average perceived level of corruption among police per region and year; Likert scale from 0 (never would do) to 4 (yes, often)	Afrobarometer
Leader (non-)autoc (non-)coup	We classify countries into coup and non-coup based on its history of coup attempts. A country is classified as coup if at least one coup attempt occured in the country within the last 30 years. Leader non-autoc coup then refers to a dummy variable that indicates the leader region of a country that is non-autocratic and has experienced at least 1 coup attempt in the last 30 years.	Archigos, PLAD, GDAM, WDPI
Leader (non-)autoc (non-)resource	We classify regions as natural-resource rich that have a least one extracting mineral mine of the 14 major minerals. Based on this definition, leader (non-)autoc (non-)resource refers to a leader region located in an (non-)autocratic country with(out) mineral mines.	Archigos, PLAD, GDAM, WDPI, Bermann (2017)
Leader (non-)autoc (non-) ethnic	We classify countries into ethnically fractionalized and homogenous by the ethnic fractionalization index of the Historical Index of Ethnic Fractionalization by Drazanova at the median. Based on this definition, leader (non-)autoc (non-)ethnic refers to a leader region in a (non-)autocratic country with an above (or below) median ethnic fractionalization index.	Archigos, PLAD, GDAM, WDPI, HIEF
	Robustness checks	
Past conflict	Provides the number of conflict years within the last three years for a given region and year.	UCDP GED
Leader autocracy / democracy / transition	Based on the polity2 variable from the Polity IV Project, we classify countries into autocracies, democracies and transition states. The polity 2 score classifies countries on a scale between -10 and 10 into democratic and autocratic. We define a system to be autocratic if polity 2 score is -5 or below and into democratic if it is 5 or above. Countries with a score inbetween are classified as transition states.	Polity IV Project
Switcher	Indicator variable which classifies countries as switchers that changed their political regime within the last 5 years.	Archigos, WDPI
Irregular entry	Indicator variable which classifies leaders by their entry into office as defined in the Archigos database.	Archigos

Appendix B

Appendix for chapter 4

B.1 Further robustness checks

TABLE B.1: Regression on 1 degree grid cells

Dependent variable	**Social conflict**	
Model	IV: Second stage	
	(1)	(2)
Δ Water mass	-0.011*	-0.038**
	(0.007)	(0.019)
Dependent variable	**Δ Water mass**	
Model	IV: First stage	
Drought months	-0.047***	-0.021***
	(0.007)	(0.004)
Kleibergen-Paap F stat	47.72	23.05
Observations	44,688	44,688
Cell FE	Yes	Yes
Year FE	Yes	
Country-year FE		Yes

Note: The table reports IV coefficients of social conflict on water mass change measured at the 1 degree grid cell level. Models include fixed effects as stated in the table. Robust standard errors are clustered at the 3 degree grid cell level.

B.2 Variable descriptions

TABLE B.2: Variable definitions

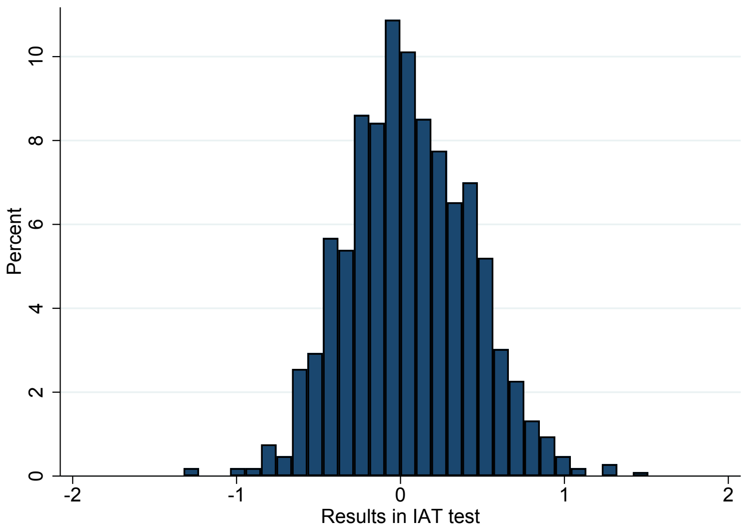
	Dependent and main variables
Social conflict	Indicator variable that takes one if in the respective year and cell a conflict event occurred, based on the SCAD conflict dataset (Salehyan et al., 2012).
State target conflict	Indicator variable that takes one if in the respective year and cell a conflict event occurred that was targeted towards the government, based on the SCAD dataset (Salehyan et al., 2012).
Non-state target conflict	Indicator variable that takes one in the respective year and cell a conflict event occurred that was not targeted towards the government, based on the SCAD conflict dataset (Salehyan et al., 2012).
Resource conflict	Indicator variable that takes one if in the respective year and cell a conflict event occurred that was triggered mainly by a natural resource issue. A resource conflict is defined as a conflict were the first, second or third mentioned issue of tension is classified as food, water, subsistence or environmental degradation. Source: Salehyan et al. (2012)
Drought months	Records the number of drought months per year and cell. A drought month is defined as a month with SPEI values below -1. Source: Vicente-Serrano et al. (2010).
	Demand and supply factors
Surface water	Indicator variable that takes one if a river or lake is located in the respective grid. Source: Natural Earth
Groundwater access	Indicator variable that takes one if groundwater is accessible. We define access by low depth to groundwater (below median) and medium to high groundwater storage (no local and shallow aquifers). Source: Fan et al. (2013) and WHYMAP from BGR
Irrigation	Indicator variable that takes one if irrigated areas are located in the cell. Source: GIAM .
Mining	Indicator variable that takes one if in the cell a major mineral deposit or a mineral extraction site is located. Source: Schulz and Briskey (2005) and Maus et al. (2020).
Urban	indicator variable that is one if any urban area is located in the grid. Source: SEDAC.
	Control variables
Temperature	Gives the average temperature in degree Celsius of a year in a cell. Source: Kalnay et al. (1996).
Meridional velocity	Gives the average wind speed in meter per second of a year in a cell from north to south. Source: Kalnay et al. (1996).
Zonal velocity	Gives the average wind speed in meter per second of a year in a cell from east to west. Source: Kalnay et al. (1996).

Appendix C

Appendix for chapter 5

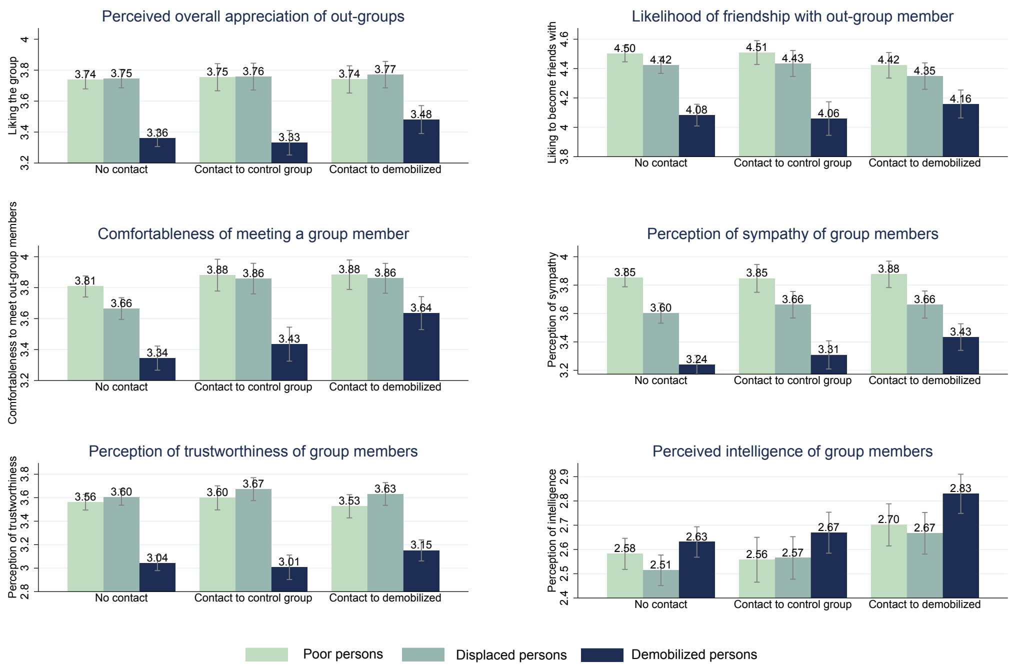
C.1 Figures

FIGURE C.1: Distribution of D-scores in the IAT-test



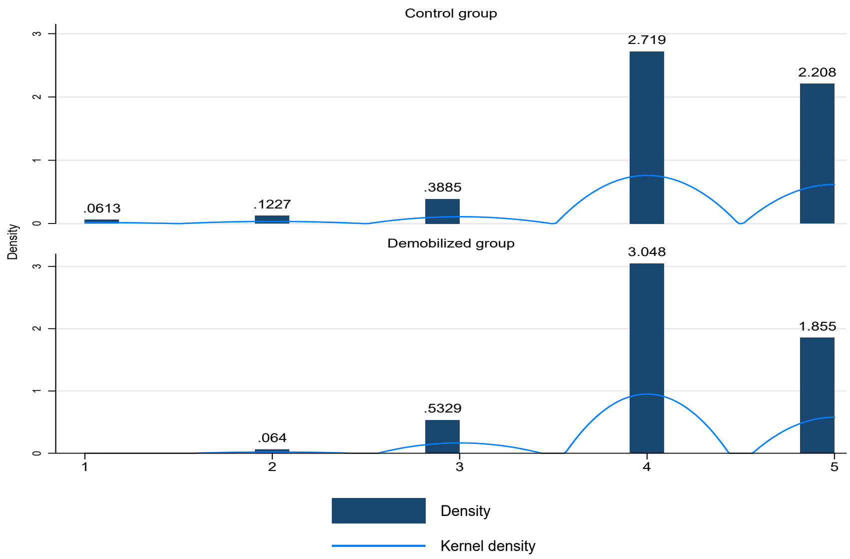
Note: The figure reports the distribution of the IAT test results.

FIGURE C.2: Stated attitudes and evaluation of the out-groups per contact treatment



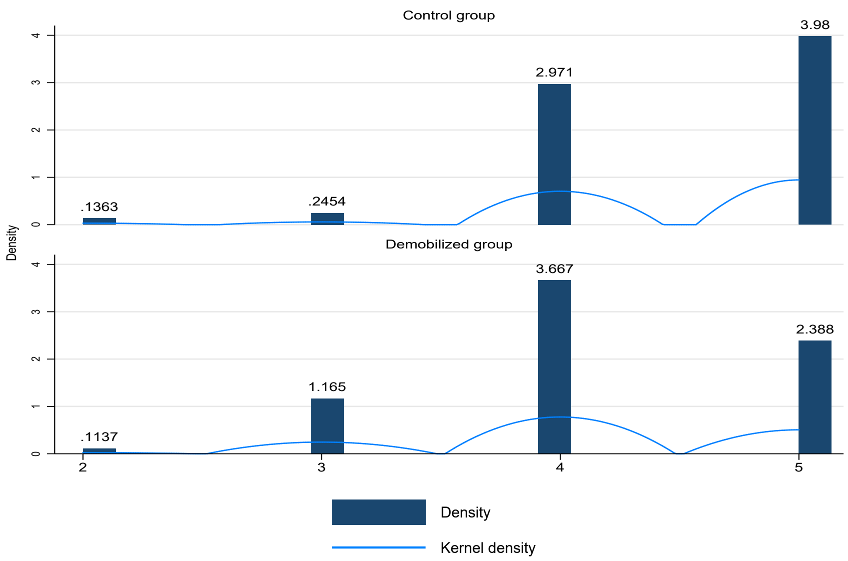
Note: The figure reports average points per contact treatment on a 5 point Likert scale on various outcomes that have been asked in the final questionnaire. In total, 1058 observations are in the treatments, whereof 531 in the no-contact treatment, 258 in the contact to demobilized treatment and 269 in the contact and non-demobilized students treatment.

FIGURE C.3: Distribution of liking the business ideas by recipient group



Note: The figure shows the distribution of the variable "liking the business ideas" in the contact treatments separately for non-demobilized and demobilized beneficiaries.

FIGURE C.4: Distribution of perceived sympathy of the persons in the videos by recipient group



Note: The figure shows the distribution of the perceived sympathy of the persons in the videos in the contact treatments separately for non-demobilized and demobilized beneficiaries.

C.2 Further data analysis and robustness checks

TABLE C.1: Balance test

	T1	T2	T3	T4	T5	T6	T7	T8	Kruskal-Wallis test (p-val)
Age	20.95	21.24	20.73	20.56	21.00	20.59	20.55	21.16	0.5
	(3.44)	(3.29)	(2.90)	(2.87)	(2.87)	(2.82)	(2.79)	(3.70)	
Female	0.48	0.35	0.47	0.46	0.42	0.42	0.40	0.43	0.48
	(0.50)	(0.48)	(0.50)	(0.50)	(0.49)	(0.50)	(0.49)	(0.50)	
Social status	3.36	3.33	3.13	3.16	3.26	3.14	3.16	2.85	0.03
	(1.24)	(1.26)	(1.26)	(1.22)	(1.22)	(1.33)	(1.27)	(1.21)	
Political orientation	3.14	3.14	3.10	3.17	3.17	3.26	3.02	3.11	0.83
	(1.16)	(1.30)	(1.15)	(1.18)	(1.28)	(1.28)	(1.21)	(1.03)	
Prosocial	0.53	0.52	0.53	0.50	0.52	0.53	0.55	0.53	0.26
	(0.13)	(0.12)	(0.13)	(0.12)	(0.14)	(0.13)	(0.13)	(0.13)	
Victimization	0.09	0.09	0.11	0.09	0.06	0.09	0.09	0.07	0.35
	(0.19)	(0.197)	(0.20)	(0.19)	(0.13)	(0.20)	(0.20)	(0.19)	

Note: The table reports the mean of socio-economic characteristics per treatment group and the Kruskal-Wallis test p-value to signal significant differences per treatment group. The respective standard deviation is shown in parenthesis below.

TABLE C.2: The full dif-in-dif model specification with control variables

	Donation				Donation amount	
	(1)	(2)	(3)	(4)	(5)	(6)
SES	0.011	0.000	-0.007	0.000	0.251	0.155
	(0.066)	(0.068)	(0.068)	(0.065)	(0.327)	(0.344)
Demobilized	0.082	0.078	0.084	0.077	0.526	0.488
	(0.059)	(0.059)	(0.061)	(0.057)	(0.320)	(0.305)
Demobilized x SES	-0.074	-0.051	-0.050	-0.049	-0.542	-0.478
	(0.078)	(0.076)	(0.076)	(0.074)	(0.457)	(0.441)
Contact	0.098	0.100	0.111	0.100	0.913***	0.879**
	(0.078)	(0.075)	(0.078)	(0.073)	(0.333)	(0.361)
Contact x SES	-0.003	-0.005	0.007	-0.004	-0.448	-0.266
	(0.101)	(0.103)	(0.106)	(0.102)	(0.575)	(0.602)
Contact x Demobilized	-0.166	-0.178*	-0.185*	-0.178*	-1.303***	-1.187**
	(0.101)	(0.098)	(0.105)	(0.096)	(0.458)	(0.462)
Contact x Demobilized X SES	0.216	0.219*	0.197	0.215*	1.801**	1.502*
	(0.132)	(0.126)	(0.131)	(0.125)	(0.757)	(0.764)
Female		0.038	0.028	0.039	-0.186	-0.304
		(0.035)	(0.036)	(0.035)	(0.211)	(0.204)
Rich		0.075*	0.069	0.076*	0.529*	0.414*
		(0.043)	(0.042)	(0.044)	(0.280)	(0.239)
Poor		-0.013	0.033	-0.012	-0.321	-0.059
		(0.035)	(0.033)	(0.034)	(0.211)	(0.205)
Left		-0.050	-0.043	-0.051	-0.479**	-0.402*
		(0.033)	(0.033)	(0.033)	(0.211)	(0.213)
Right		-0.010	-0.021	-0.011	-0.654	-0.958**
		(0.085)	(0.090)	(0.081)	(0.436)	(0.427)
Cali		-0.063		-0.062	-0.501	
		(0.044)		(0.043)	(0.309)	
Religious		0.011	0.011	0.011	0.128***	0.119***
		(0.009)	(0.009)	(0.009)	(0.043)	(0.041)
Prosocial		0.615***	0.637***	0.622***	3.774***	3.661***
		(0.110)	(0.105)	(0.110)	(0.758)	(0.770)
Victimization		0.006	-0.028	0.010	0.508	0.310
		(0.075)	(0.080)	(0.074)	(0.527)	(0.559)
Support peace process		0.060***	0.062***	0.059***	0.321***	0.306**
		(0.016)	(0.017)	(0.016)	(0.114)	(0.118)
Age		-0.002	0.004	-0.002	0.010	0.065
		(0.005)	(0.006)	(0.005)	(0.032)	(0.039)
Observations	1,058	1,058	1,058	1,058	1,058	1,058
R-squared	0.012	0.073	0.134		0.091	0.170
Subject of study FE	Yes	Yes	Yes	Yes	Yes	Yes
Session FE			Yes			Yes
Probit model				Yes		

Note: The table reports estimation results from regressing the discrimination outcomes on the treatment dummies as well as its interactions. The regressions include controls as shown in the table. Fixed effects are included as indicated in the table. Clustered standard errors at the session level are in parenthesis, ***,**,* denote significance at 1, 5 and 10%.

TABLE C.3: Perceived attitudes towards the recipient groups

	Liking	**Encounter**	**Friend**	**Sympathy**
	(1)	(2)	(3)	(4)
Demobilized	-0.431***	-0.497***	-0.391***	-0.405***
	(0.074)	(0.124)	(0.080)	(0.063)
SES	-0.035	-0.032	-0.021	-0.051
	(0.057)	(0.092)	(0.080)	(0.071)
Demobilized x SES	-0.006	0.094	-0.076	-0.036
	(0.075)	(0.141)	(0.089)	(0.090)
Contact	-0.024	0.014	-0.045	-0.041
	(0.063)	(0.092)	(0.090)	(0.086)
Contact x SES	0.027	0.015	0.049	0.016
	(0.081)	(0.133)	(0.133)	(0.094)
Contact x Demobilized	0.181*	0.290*	0.114	0.141
	(0.096)	(0.164)	(0.107)	(0.103)
Contact x Demobilized x SES	-0.085	-0.157	-0.073	-0.025
	(0.104)	(0.189)	(0.157)	(0.127)
Total: Contact x Demobilized x SES	0.157*	0.304**	0.069	0.100
	(0.064)	(0.103)	(0.084)	(0.071)
Observations	1,058	1,058	1,058	1,058
R-squared	0.300	0.199	0.204	0.235
Subject of study FE	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes

Note: The table reports estimation results from regressing the diverse stated perception of the recipient group in the final questionnaire on a full set of treatment dummies and its interactions. *Encounter* gives the comfortableness in meeting a recipients' group member on a 5 point Liker scale; *Friend* refers to the likelihood of becoming friends with a recipient group member and *Sympathy* refers to the overall liking of the recipient group all measured on a 5 point Liker scale. The *Liking index* is the index constructed out of these 3 items. The regressions include controls as shown in table C.2. Fixed effects as indicated in the table. Clustered standard errors at the session level are in parenthesis, ***,**,* denote significance at 1, 5 and 10%.

TABLE C.4: The effects of contact controlling for perceptions of the contact situation

	Donated	**Donation amount**	**Liking index**	**IAT-test**
	(1)	(2)	(3)	(4)
Contact x SES	0.010	-0.088	-0.002	0.020
	(0.063)	(0.435)	(0.069)	(0.047)
Contact x Demobilized	-0.060	-0.281	0.165***	-0.016
	(0.070)	(0.424)	(0.047)	(0.055)
Contact x Demobilized x SES	0.133	0.845	-0.002	0.062
	(0.094)	(0.546)	(0.088)	(0.068)
Liking business idea	0.116***	0.623***	0.028	-0.010
	(0.029)	(0.169)	(0.038)	(0.025)
Perception hard working	0.014	-0.034	0.007	-0.002
	(0.045)	(0.338)	(0.051)	(0.039)
Perception neediness	0.004	-0.011	-0.022	0.019
	(0.022)	(0.130)	(0.027)	(0.018)
Perception hostility	-0.015	-0.173	-0.028	-0.032**
	(0.015)	(0.112)	(0.020)	(0.013)
Perception trustworthiness	0.035	-0.107	0.013	0.007
	(0.044)	(0.265)	(0.055)	(0.029)
Perception sympathy	0.052	0.760***	-0.067	0.000
	(0.037)	(0.261)	(0.044)	(0.043)
Total effect: Contact x Demobilized x SES	0.073	0.564	0.163*	0.046
	(0.059)	(0.369)	(0.066)	(0.046)
Observations	527	527	527	527
R-squared	0.234	0.257	0.271	0.159
Subject of study FE	Yes	Yes	Yes	Yes
Session FE	Yes	Yes	Yes	Yes

Note: The table reports estimation results from regressing the 4 discrimination outcomes on the treatment dummies as well as its interaction terms. The regressions include controls as shown in table C.2 as well as perceptions of the video. Fixed effects are included as indicated in the table. The sample consists out of 527 observations that have been in the contact treatments. Clustered standard errors at the session level are in parenthesis, ***,**,* denote significance at 1, 5 and 10%.

C.3 Variable definitions

TABLE C.5: Variable definitions

Variable	**Description**
Age	Age of the respective participant in years
Cali	Dummy that indicates that the experiment has taken place in Cali
Contact	Dummy variable that is one if the participant is in a contact treatment
Demobilized	Dummy variable that is one if the participant can donate to the demobilized recipients
Donation	Dummy variable that is one if the participant has donated
Donation amount	Gives the amount of donation in 1000 COP
Encounter	Gives the degree of comfortableness of meeting a member of the recipient group (demobilized person or poor person) on a 5 point Likert scale
Female	Dummy variable that is one if the participant is female
Friend	Gives the likelihood of becoming friends with a member of the recipient group (demobilized person or poor person) on a 5 point Likert scale.
IAT-test	Gives the D-score that is constructed using the response time and error rates in the IAT test.
Left	We ask participants to state their political orientation on a Likert scale from 1 to 7 and afterwards classified left oriented for values 1 and 2 referred to as "very left wing" and "left wing"
Liking (index)	Liking is an index constructed out of the 3 items: "How comfortable would you feel meeting … (a demobilized, a poor, a displaced person)." "How likely is it that you become friends with .." "How much do you overall like the group x". Each item was answered on a 5 point Likert scale. The liking index gives the index given to the respective beneficiary group demobilized or poor persons.
Liking business idea	Gives the subjective liking of the business ideas presented in the video in the contact situation on a 5 point Liker scale.
Perception of hard working person	Gives the subjective evaluation of how hard working the persons are presented in the video in the contact situation on a 5 point Likert scale.
Perception of sympathy	Gives the subjective evaluation of how sympathetic the persons are presented in the video in the contact situation on a 5 point Likert scale

Perception of neediness	Gives the subjective evaluation of how needy the persons are presented in the video in the contact situation on a 5 point Likert scale
Perception of hostility	Gives the subjective evaluation of how hostile the persons are presented in the video in the contact situation on a 5 point Likert scale
Perception of trustworthiness	Gives the subjective evaluation of how trustworthy the persons are presented in the video in the contact situation on a 5 point Likert scale
Private	Dummy variable that is one for sessions at a private university
Prosocial	Prosocial is a normalized index constructed out of the following items: We ask participants in the final survey to agree or disagree on a 5 point Likert scale to the statement: "In general, one should help people in need.", "Everyone deserves a second chance." "One should receive what one has worked for." "Everyone is responsible for his/her own life." Additionally, we ask the participants how often they have done the following activities: voluntary work, donating, helping neighbors. We take this as an indicator of prosociality.
Poor	Dummy variable that is one if the participant lives in a social strata of 1 or 2
Religious	We ask participants to state how religious they rank themselves on a Likert scale of 1 to 7.
Rich	Dummy variable that is one if the participant lives in a social strata of 5 or 6
Right	We ask participants to state their political orientation on a Likert scale from 1 to 7 and afterwards classified left oriented for values 6 and 7 referred to as "very right wing" and "right wing".
SES	Dummy variable that is one if participant is in the SES treatment
Support peace process	We ask participants in the final survey to agree or disagree on a 5 point Likert scale to the statement: "I support the last peace process." We take this as an indicator of the attitude towards the peace process. Higher values represent a higher agreement with the peace process.
Sympathy	Gives the overall liking of the recipient group (demobilized persons or poor persons) on a 5 point Likert scale
Victimization	Based on the answers of "Have you been victimized in the following sense: Displacement, Torture/fighting and kidnapping" we construct an indicator that is 0 (not victimized) if all three questions have been answered with no; 1 (victimized) if at least one question is answered with yes and 2 (strongly victimized) if more than one question is answered with yes.

C.4 Instructions

TABLE C.6: Experiment instructions and questionnaire

Introduction

Dear participant,

Thanks a lot for your willingness to participate in our study that is about perceptions and attitudes. The participation in this study is voluntary.

At the end of the study, we will pay you in cash for your participation. The payment consists out of a fixed show-up fee (5.000 COP) and a variable amount depending on your actions and decisions in the study.

Please read carefully through all of the instructions. In total, the study takes around 45 minutes.

Thank you once more for participating.

Declaration of consent

Please read carefully the following points**:**

1. I approve to participate voluntarily in this study.
2. I understand that the collected data are used for scientific research only.
3. I approve to be asked about my opinion, emotions and perceptions towards different persons and situations.
4. I understand that this can affect my mood.
5. I approve the use of my data in an anonymous form.

I have understood all the mentioned points above and I declare my consent to participate in this experiment.

Yes No

Anonymous code

Your data will be saved and identified with a code. Please follow the following instructions to create the code.

First letter of your surname

First letter of your mother's surname

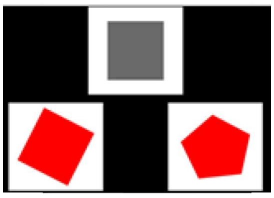
Numbers of the day you were born

Last letter of the city you were born

Part 1: Classification task

Classification task

Your task is to classify objects.



In the following task, you will see 3 objects. Please choose the object that represents a rotation of the object above. Please click on the correct object with the mouse.

In the following, we will provide you with some examples.

The payment in this task depends on your performance. If you succeed in classifying 15 objects correctly, you will receive 10.000 COP.

Classification task

In the following, there are 3 rounds of practice. These rounds do not affect your final payment.

Please press the space bottom to continue.

Classification task

The practice round is over.

Please start with the real task. Your performance will now affect the amount of money you will receive afterwards.

Please press the space bottom to continue.

Classification task

The task is over. You have gained 10.000 [0] COP.

Please press the space bottom to continue.

Part 2: Video

In the following, we ask you to watch a (two) video(s), in which you will get to know the institution SENA [and some (demobilized) persons that study in SENA].

Please pay attention to the video(s).

After the video(s), we will ask you some questions regarding the content of the video and your perceptions.

Video

Control questions

1. How attentive have you watched the video?
   Very attentive -------------------------------- Very inattentive

2. About which institution they are talking in the video?
   SENA – University of Javeriana – Agency of reintegration

3. How do you perceive the institution SENA?
   Trustworthy Efficient
   Good Useful
   Likert scale: A lot ------------------------------------ Not at all

---

Donation

The students of SENA are searching for funding to realize their business ideas.

Who are they?

They are [demobilized] persons who are studying a 1-year technical formation program in SENA.

[They are parents, between 45 and 60 years old. All have completed a technical formation degree and have some working experiences in different simple tasks.]

Do you want to make a donation to support their business ideas?

Yes No

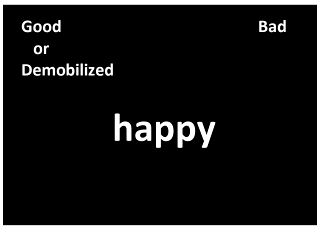
How much do you want to donate from the money you have gained in the task before?

- 1.000 COP - 6.000 COP
- 2.000 COP - 7.000 COP
- 3.000 COP - 8.000 COP
- 4.000 COP - 9.000 COP
- 5.000 COP - 10.000 COP

Part 3: Implicit association test

Classification task

In this part, we will present you words and images. Your task consists out of classifying the words and pictures into the corresponding categories. The task consists out of two rounds. In each round, there will be a practice round to start with.



Please classify the object in the center of the screen with the categories written down on the top of the screen using the keyboard.

To classify with categories on the right of the screen use the letter I.

To classify with categories on the left of the screen use the letter E.

Please respond as fast as you can intending to make no errors. If your respond is incorrect, an X will appear on the screen.

Classification task

Please collect your fingers on the letters E and I.

If you see in the center of the screen…

… a word that is associated with **good** things, you have to press the letter **E.**

… a picture that is associated with **demobilized persons**, you have to press the letter **E.**

... a word that is associated with **bad** things, you have to press the letter **I.**

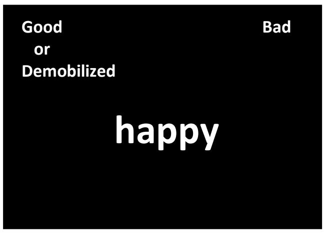
We will start with a practicing round.

Press the space bottom to continue.

Classification task

The practicing round is over. Please start with the real task.

If you see ….



A **good** word, press the letter **E**.

An image of a **demobilized person**, press the letter **E**.

A **bad** word, press the letter **I**.

Press the space bottom to continue.

Classification task

Please collect your fingers on the letters E and I.

If you see in the center of the screen…

… a word that is associated with **good** things, you have to press the letter **E.**

… a picture that is associated with **demobilized persons**, you have to press the letter **I.**

... a word that is associated with **bad** things, you have to press the letter **I.**

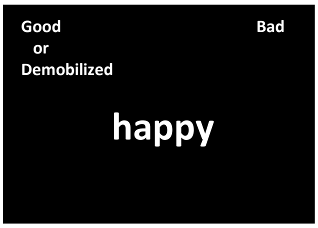
We will start with a practicing round.

Press the space bottom to continue.

Classification task

The practicing round is over. Please start with the real task.

If you see ….



A **good** word, press the letter **E**.

An image of a **demobilized person**, press the letter **I**.

A **bad** word, press the letter **I**.

Press the space bottom to continue.

Classification task

The task is over.

Press the space bottom to continue.

<u>Part 4: Questionnaire</u>

To finalize, we have some questions regarding your personal characteristics and opinions. Please choose the answer that fits the best to your case.

Questionnaire

1. What is your gender?
   Feminine masculine other

2. How old are you?
   Your age _____________

3. What is your nationality?
   Your nationality: ______________________

4. In which city and region have you lived the longest in your life?
   City: ____________________
   Region: _______________

5. What is your study subject?
   Arts
   Health studies
   Economics
   Social sciences
   Humanities
   Administration / Business
   Natural sciences
   Politics
   Engineering

6. In which social strata do you live?

1	4
2	5
3	6

7. How do you evaluate your economic situation?
   Very good – god – nor good nor bad – bad – very bad

8. Often political preferences are classified in terms of right and left wing. On such a scale, how would you classify your personal political preferences?
   Very right wing – right – center – left –very left wing

9. Do you consider yourself as a religious person?
   Very religious-- Not at all religious

Empathy + taking perspective

1. How strong do you agree or disagree with the following statements?
   a. In general, it is easy for me to understand the arguments and viewpoints of other people.
   b. I easily can feel the emotions of others.
   c. I have asked myself different times, how various actors in the armed conflict in Colombia must have felt.

   (Agree a lot, agree, nor agree nor disagree, disagree, disagree a lot)

Optimism and openness

1. How strong do you agree or disagree with the following statements?
   - It is easy for me to talk to strangers.
   - Even in difficult situations, I think positively.
   - In general, I think there are more good than bad things happening in the world.
   - I am more reserved than social.
     (Agree a lot, agree, nor agree nor disagree, disagree, disagree a lot)

Altruism / pro-sociality

1. How often have you done the following activities in the last year?
   - Voluntary work without compensation
   - Donating
   - Helping neighbors
     (Never, once, a few times, once a month, a few times a month, dairy)

Social norms

How strong do you agree or disagree with the following statements?

- Everyone deserves a second chance.
- One should receive what one has worked for.
- In general, one should help the people in need.
- Everyone is responsible for his/her own life. Everyone should look after him/herself.
- In general, I belief the majority of the poor people are poor because of their own decisions.

(Agree a lot, agree, nor agree nor disagree, disagree, disagree a lot)

Attitudes towards the outgroup

1. How strong do you agree or disagree with the following statements?
   - I support the last peace process.
   - It is fair that the government is helping the demobilized people economically.
   - I don't want to live close by demobilized people.
   - I disapprove that the state is helping the demobilized people, because I belief they should take the consequences of their own actions.

   (Agree a lot, agree, nor agree nor disagree, disagree, disagree a lot)

Perceptions of outgroup

1. How do you evaluate the intelligence of the following groups?
   Students, Demobilized people, Displaced people, Poor persons
   Very above average – above average – average - below average – very below average

2. How much do you like the following groups?
   Students, Demobilized people, Displaced people, Poor persons
   Liking a lot – liking - nor liking nor disliking – disliking - disliking a lot

3. How do you perceive the poor people?
   Trustworthy, sympathetic, hostile, hardworking, needy
   A lot -------------------------------------- not at all

4. How do you perceive the demobilized people?
   Trustworthy, sympathetic, hostile, hardworking, needy
   A lot -------------------------------------- not at all

5. How do you perceive the displaced people?
   Trustworthy, sympathetic, hostile, hardworking, needy
   A lot -------------------------------------- not at all

Intergroup anxiety

1. How comfortable do you feel meeting a member of the following groups:
   Students, Demobilized people, Displaced people, Poor persons
   Very comfortable – comfortable- nor comfortable nor uncomfortable- uncomfortable – very uncomfortable

Behavioral change

1. How likely is it, that you will become friends with
    - A demobilized person that studies with you?
    - A poor person that studies with you?
    - A displaced person that studies with you?

   Very likely – likely- nor likely nor unlikely – unlikely- very unlikely

Learning about the out-group

How would you evaluate your knowledge about…
- The armed conflict in Colombia?
- The reintegration process of demobilized people?
- The organization SENA?

Very good – good – nor good nor bad – bad – very bad

Victimization

1. Have you been victim in the following senses?
    - Displacement
    - Terrorist attacks / fighting / landmines / torture
    - Extortion / kidnapping
    - Sexual delicts
    - Homicides of family members or close friends
    - None of these situations

Attachment

2. Do you know a person
    - That has been / is member of a guerrilla group?
    - That has been / is member of a paramilitary group?
    - That has been/ is very poor?

   Yes No

Video perceptions

1. Have the stories presented in the video moved you emotionally?
   A lot -------------------------------------- not at all

2. How much do you like the business ideas of the persons in the video?
   A lot -------------------------------------- not at all

3. How much do you like the business idea of Marisol/Criselia?
   A lot -------------------------------------- not at all

4. How much do you like the business idea of Paulino/Ramiro?
   A lot -------------------------------------- not at all

5. How do you perceive the persons in the video with respect to the following characteristics?
    - Trustworthy
    - Sympathetic

- Hostile
- Hard-working
- Needy

A lot -------------------------------------- not at all

6. How do you like Marisol/Ciselia?
   A lot -------------------------------------- not at all

7. How do you like Paulino/Ramiro?
   A lot -------------------------------------- not at all

End

The study is over. Thanks a lot for you participation

TABLE C.7: Interview guideline of the videos

Part 1: Presentation of the person

Personal facts:

What is your name?

How old are you?

Where do you come from?

Personality and interests:

Name two positive personal characteristics or behavior that describe you well and describe a typical situation in which these characteristics are visible.

What makes you happy?

What are topics, you are interested in?

What are the three most important values for you?

Experiences / Life story:

What have you done so far and what are you doing now? / What is your life narrative story?

Part 2: Business idea

Please present us your Business idea

What kind of business do you want to open and why?

What is it that would make you happy in this job?

Who are your targeted clients and market?

What do you think is the social impact of your business?

What qualifies you for this job/business opening?

What have you already done so far to fulfill the idea and what are the next steps that you need to do?

For what do you need the credit? How would you use the money?

What are your future plans/visions?

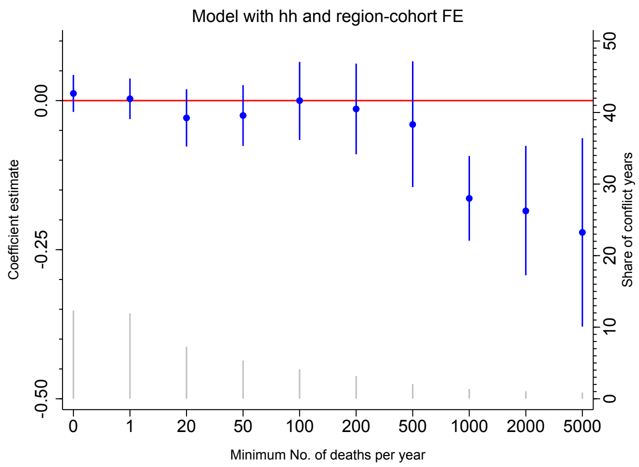
Note: The interview guideline served as a base of the video content and as a pillar for the interviewees. The persons were asked to answer these questions, but not all answers and questions are in the final video.

Appendix D

Appendix for chapter 6

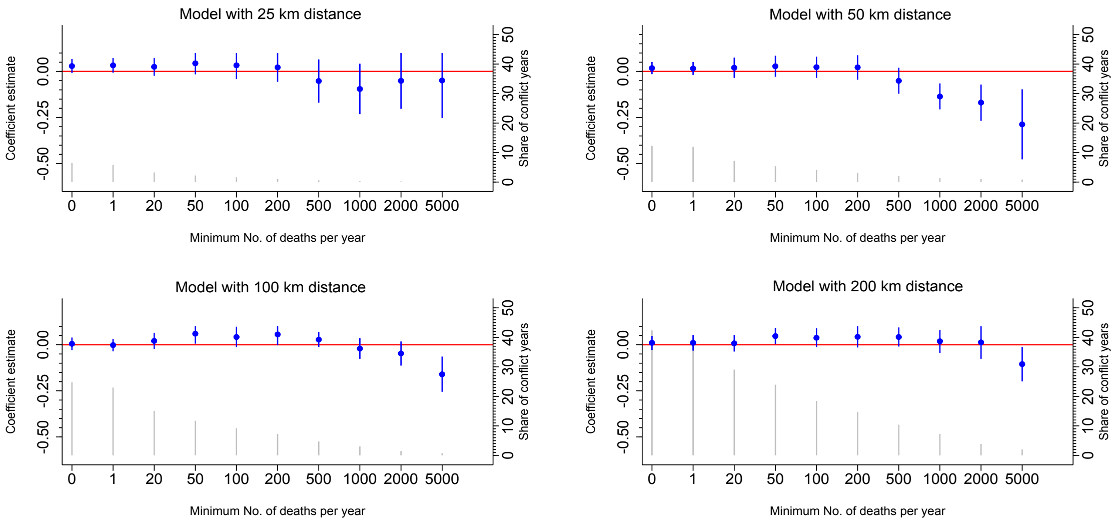
D.1 Figures

FIGURE D.1: Robustness: The effects of past conflict exposure on education with region-cohort fixed effects



Note: The figure reports point estimates and 95% confidence intervals of education on conflict exposure (from in utero to age 12) within 50 km to the survey location. The regressions include weather controls, gender-age fixed effects and household combined with regional cohort fixed effects.. $N = 480,847$. The threshold that defines a severe conflict-year varies according to a minimum number of battle-related deaths displayed horizontally. The share of observations with at least one conflict year using the given deaths threshold is depicted by grey bars (second vertical axis). Standard errors are clustered at the level of administrative regions.

FIGURE D.2: Robustness: The effects of past conflict exposure on education at 25, 50, 100 and 200 km distance



Note: The figure reports point estimates and 95% confidence intervals of the regression from education on conflict exposure (from in utero to age 12) within 25, 50, 100 and 200 km to the survey location. The regressions include weather controls, gender-age fixed effects as well as household and regional cohort fixed effects as stated in the graphs. $N = 480,847$. The threshold that defines a severe conflict-year varies according to a minimum number of battle-related deaths displayed horizontally. The share of observations with at least one conflict year using the given deaths threshold is depicted by grey bars (second vertical axis). Standard errors are clustered at the level of administrative regions.

D.2 Further data analysis and robustness checks

TABLE D.1: Intensity of conflict and education by age periods

	Years of education	
	(1)	(2)
Moderate-intensity conflict in utero	0.012	-0.002
	(0.027)	(0.028)
Moderate-intensity conflict years at age 0–3	0.011	0.010
	(0.020)	(0.019)
Moderate-intensity conflict years at age 4–6	0.010	0.015
	(0.024)	(0.026)
Moderate-intensity conflict years at age 7–12	0.028	0.026
	(0.024)	(0.022)
High-intensity conflict in utero	-0.171**	-0.127*
	(0.077)	(0.074)
High-intensity conflict years at age 0–3	-0.157***	-0.126***
	(0.054)	(0.047)
High-intensity conflict years at age 4–6	-0.226***	-0.145**
	(0.068)	(0.060)
High-intensity conflict years at age 7–12	-0.089	-0.022
	(0.117)	(0.083)
Observations	541,480	480,847
R-squared	0.550	0.772
Gender-age FE	Yes	Yes
Weather controls	Yes	Yes
Country-cohort FE	Yes	Yes
Location FE	Yes	
Household FE		Yes

Note: The table reports estimation results from regressing education on the number of moderate- and high-intensity conflict years (between in utero and age 12) per age period. Conflict events are counted if occurred within 50 km to the survey. Moderate-intensity conflict years refer to years with less than 1000 deaths; high-intensity years to 1000 and more deaths. Standard errors are clustered at the level of administrative region. , ***,**,* denote significance at 1, 5 and 10%.

TABLE D.2: Intensity of conflict and education by gender

	Years of education	
	(1)	(2)
Moderate-intensity conflict years	0.032*	0.033*
	(0.018)	(0.018)
Moderate-intensity conflict years × Female	-0.025**	-0.032***
	(0.010)	(0.010)
High-intensity conflict years	-0.222***	-0.185***
	(0.050)	(0.040)
High-intensity conflict years × Female	0.124**	0.143***
	(0.049)	(0.052)
Observations	541,480	480,847
R-squared	0.551	0.772
Gender-age FE	Yes	Yes
Weather controls	Yes	Yes
Country-cohort FE	Yes	Yes
Location FE	Yes	
Household FE		Yes

Note: The table reports estimation results from regressing education on the number of moderate- and high-intensity conflict years (between in utero and age 12) as well as its interaction with a female dummy. Conflict events are counted if occurred within 50 km to the survey. Moderate-intensity conflict years refer to years with less than 1000 deaths; high-intensity years to 1000 and more deaths. Standard errors are clustered at the level of administrative region. , ***,**,* denote significance at 1, 5 and 10%.

TABLE D.3: Robustness: Share of migrants and past conflict

	Share of migrants in location	
	(1)	(2)
Conflict years	0.004	
	(0.002)	
Moderate-intensity conflict years		0.003
		(0.002)
High-intensity conflict years		0.012***
		(0.003)
Observations	8,329	8,329
R-squared	0.087	0.088
Year FE	Yes	Yes

Note: The table reports estimation results from regressing the share of migrants among youth of age 10-26 in a survey location on the number of conflict years in the last 25 years, including further controls as stated in the table. Conflict events are counted if occurred within 50 km to the survey location. Moderate-intensity conflict years refer to years with less than 1000 deaths; high-intensity years to 1000 and more deaths. ***,**,* denote significance at 1, 5 and 10%.

TABLE D.4: Robustness: Differences in socio-economic status by migration status

	Years of education	**Highest educ. in hh.**	**Poor hh.**	**Rich hh.**
	(1)	(2)	(3)	(4)
Non-migrant	-0.046*	-0.111***	0.031***	-0.051***
	(0.027)	(0.010)	(0.004)	(0.004)
Observations	68,110	68,110	68,110	68,110
R-squared	0.511	0.468	0.425	0.430
Gender-age FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes
Country-cohort FE	Yes	Yes	Yes	Yes

Note: The table reports estimation results from regressing socio-economic variables on the a dummy variable of non-migrants on a sub-sample with migration information. ***,**,* denote significance at 1, 5 and 10%.

TABLE D.5: Robustness: Conflict exposure and education by migration status

	Years of education			
	(1)	(2)	(3)	(4)
Moderate-intensity conflict years	-0.035	-0.061	-0.132***	-0.193*
	(0.039)	(0.080)	(0.050)	(0.101)
High-intensity conflict years	-0.624***	-0.167	-0.213	-0.098
	(0.188)	(0.256)	(0.227)	(0.262)
Moderate-intensity conflict years × Non-migrant hh.			0.109***	0.148***
			(0.032)	(0.048)
High-intensity conflict years × Non-migrant hh.			-0.509***	-0.087
			(0.191)	(0.337)
Non-migrant hh.			-0.057	0.074
			(0.050)	(0.070)
Observations	68,110	37,962	68,110	37,962
R-squared	0.502	0.767	0.502	0.767
Gender-age FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Country-cohort FE	Yes	Yes	Yes	Yes
Location FE	Yes		Yes	
Household FE		Yes		Yes

Note: The table reports estimation results from regressing education on the number of moderate- and high-intensity conflict years (between in utero and age 12) for a sub-sample with data on migration experiences. Specifications include fixed effects and further controls as stated in the table. Conflict events are counted if occurred within 50 km to the survey location. Moderate-intensity conflict years refer to years with less than 1000 battle-related deaths; high-intensity years to 1000 and more deaths. ***,**,* denote significance at 1, 5 and 10%.

TABLE D.6: Robustness: Placebo conflict exposure

	Years of education			
	(1)	(2)	(3)	(4)
Moderate-intensity conflict years in pre-utero	0.055	0.061		
	(0.043)	(0.043)		
High-intensity conflict years in pre-utero	-0.049	-0.053		
	(0.039)	(0.041)		
Moderate-intensity conflict years age 20-25			0.016	0.058***
			(0.012)	(0.020)
High-intensity conflict years age 20-25			0.066	-0.010
			(0.046)	(0.071)
Observations	441,773	363,817	652,003	362,665
R-squared	0.562	0.781	0.545	0.836
Gender-age FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Country-cohort FE	Yes	Yes	Yes	Yes
Location FE	Yes		Yes	
Household FE		Yes		Yes

Note: The table reports estimation results from regressing education on the number of moderate- and high-intensity conflict years (two years before in utero and during age 20-25). Specifications include fixed effects and further controls as stated in the table. Conflict events are counted if occurred within 50 km to the survey location. Moderate-intensity conflict years refer to years with less than 1000 deaths; high-intensity years to 1000 and more deaths. ***,**,* denote significance at 1, 5 and 10%.

TABLE D.7: Robustness: Conflict exposure with differently clustered standard errors

Dependent:s	Years of education					
	(1)	(2)	(3)	(4)	(5)	(6)
Clustering standard errors:	Location		Location & country-cohort		Spatially corrected	
Moderate-intensity conflict years	0.019*	0.017	0.019	0.017	0.019	0.017
	(0.010)	(0.010)	(0.015)	(0.013)	(0.018)	(0.017)
High-intensity conflict years	-0.161***	-0.116***	-0.161***	-0.116***	-0.161***	-0.116**
	(0.036)	(0.036)	(0.050)	(0.043)	(0.054)	(0.051)
Observations	541,480	480,847	541,480	480,847	541,480	480,847
R-squared	0.550	0.772	0.550	0.772	0.031	0.029
Gender-age FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes		Yes		Yes	Yes
Household FE		Yes		Yes		Yes

Note: The table reports estimation results from regressing education on the number of moderate- and high-intensity conflict years (between in utero and age 12). Specifications include fixed effects and further controls as stated in the table. Conflict events are counted if occurred within 50 km to the survey location. Moderate-intensity conflict years refer to years with less than 1000 battle-related deaths; high-intensity years to 1000 and more deaths. Models vary in the specification of standard errors. , ***,**,* denote significance at 1, 5 and 10%.

D.3 Sample and variable description

TABLE D.8: List of DHS surveys

Angola (2015/2016), Benin (2001, 2011/2012), Burundi (2010, 2012), Burkina Faso (2003, 2010), Cameroon (2004, 2011), Chad (2014/2015), Comoros (2012), DR Congo (2007, 2013/2014), Ethiopia (2005, 2011, 2016), Gabon (2012), Ghana (2003, 2008, 2014), Guinea (2005, 2012), Ivory Coast (2011/2012), Kenya (2003, 2008/2009, 2014), Lesotho (2009, 2014), Liberia (2007, 2013), Madagascar (2008/2009), Mali (2001, 2006, 2012/2013), Malawi (2000, 2004, 2010, 2015/2016), Mozambique (2009, 2011), Namibia (2000, 2006/2007, 2013), Nigeria (2003, 2008, 2013), Rwanda (2005, 2010, 2014/2015), Senegal (2005, 2010/2011, 2012/2013, 2015), Sierra Leone (2013), Swaziland (2006/2007), Tanzania (2010, 2015/2016), Togo (2013/2014), Uganda (2000/2001, 2006, 2011), Zambia (2007, 2013/2014), Zimbabwe (2005/2006, 2010/2011, 2015)

TABLE D.9: Variable definitions

Dependent and main variables	
Years of education	Records the reported individual educational attainment in years.
Gender-age FE	Full set of interactions between age indicators and the reported gender.
Conflict years (in utero, at age of 0–3, 4–6, 7–12)	Measures conflict exposure of an individual in years, from the year before the birth year (in utero) until the age of 12 (or within the stated age brackets). A conflict year is defined as a year in which at least one conflict event has taken place within 50 km distance to the respective survey location.
Conflict years by severity (x deaths)	Measures conflict exposure of an individual in years, from the year before the birth year (in utero) until the age of 12 (or within the stated age brackets). A conflict year is defined as a year with at least x battle-related deaths occurring within 50 km distance to the respective survey location.
Moderate-intensity conflict years	Measures conflict exposure of an individual in years from the year before the birth year (in utero) until the age of 12 years. A moderate-intensity conflict year is a year with less than 1000 battle related deaths. Conflict events are counted within 50 km distance to the respective survey location.
High-intensity conflict years	Measures conflict exposure of an individual in years from the year before the birth year (in utero) until the age of 12 years. A high-intensity conflict year is a year with 1000 or more battle related deaths. Conflict events are counted within 50 km distance to the respective survey location.
Drought months (in utero, at age of 0–3, 4–6, 7–12)	Measures the exposure to drought events of an individual in months, from one year before the birth year until the age of 12 (or within the stated age brackets). A drought month is defined as a year when 12-months scale SPEI index is lower than -1.5.
Wet months (in utero, at age of 0–3, 4–6, 7–12)	Measures the exposure to extreme wet months of an individual from one year before the birth year until the age of 12 (or within the stated age brackets) in months. A wet month is defined as a year when the 12-months SPEI index was above 1.5.

Instrumental variable approach	
Distance to border	The variable gives the geographical distance to the nearest ethnic border in 100 km.
Distance to admin. center	The variable measures the geographical distance to the regional capital in 100 km (second administrative level).
Heterogeneity analysis	
Asinh(Conflict deaths)	Inverse hyperbolic sine function of the total number of battle-related deaths that occurred in 50 km distance to the survey location of an individual between one year before the birth and the age of 12.
Asinh(State conflict deaths)	Inverse hyperbolic sine function of the total number of battle-related deaths in conflicts where a state actor was involved. Conflict events are counted if occurred in 50 km distance to the survey location of an individual between one year before the birth and the age of 12. Conflict type is based on the UCDP classification.
Asinh(Non-state conflict deaths)	Inverse hyperbolic sine function of the total number of battle-related deaths in conflicts where no state actor was involved. Conflict events are counted if occurred in 50 km distance to the survey location of an individual between one year before the birth and the age of 12. Conflict type is based on the UCDP classification.
Asinh(One-sided conflict deaths)	Inverse hyperbolic sine function of the total number of battle-related deaths in conflicts with one-sided violence. Conflict events are counted if occurred in 50 km distance to the survey location of an individual between one year before the birth and the age of 12. Conflict type is based on the UCDP classification.
Higher ethnic frac.	Dummy variable that is one if the ethnic fractionalization index of the country is above the median.
Strong democracy	Dummy variable that is one if the polity2 score of the country is in more than 10 years of all years above 5.
Strong autocracy	Dummy variable that is one if the polity2 score of the country is in more than 10 years of all years below -5.
Higher income per capita	Dummy variable that is one if the average adjusted net national income per capita over 1989-2015 (current US$) is above the median
Natural resources	Dummy variable indicating that within 50 km of the survey location there is a natural resources deposit
More nightlights	Dummy variable that is one if the logarithm of the average nightlight intensity over time (1992-2013) of the grid is above the median.

Declaration for admission to the doctoral examination

I, Kerstin Unfried, confirm

- that the dissertation "The causes and consequences of violent conflict" that I submitted was produced independently without assistance from external parties, and not contrary to high scientific standards and integrity,
- that I have adhered to the examination regulations, including upholding a high degree of scientific integrity, which includes the strict and proper use of citations so that the inclusion of other ideas in the dissertation are clearly distinguished,
- that in the process of completing this doctoral thesis, no intermediaries were compensated to assist me neither with the admissions or preparation processes, and in this process,
  - No remuneration or equivalent compensation were provided
  - No services were engaged that may contradict the purpose of producing a doctoral thesis
- that I have not submitted this dissertation or parts of this dissertation elsewhere.
- I am aware that false claims (and the discovery of those false claims now, and in the future) with regards to the declaration for admission to the doctoral examination can lead to the invalidation or revoking of the doctoral degree.

Signed: ____

Date: ____

Author contributions

The main part of the thesis build on four research papers. The contributions to each have been divided among all co-authors as follows:

Sending peace home?! The effects of political favoritism on conflict
The project is co-authored with Andreas Kammerlander. We have equally contributed to the research design, the data preparation and analysis, and the writing of the manuscript.

Water scarcity and conflict
The research project is co-authored with Krisztina Kis-Katos and Tilman Poser. All authors contributed to the research design and the writing of the manuscript. Tilman Poser and I did the data preparation and analysis. Krisztina Kis-Katos and I interpreted the results. Krisztina Kis-Katos supervised the research project.

Discrimination and inter-group contact in post-conflict settings: Experimental evidence from Colombia
The research project is co-authored with Marcela Ibañez Diaz and Lina Maria Restrepo Plaza. All authors contributed to the conceptualization of the research idea, the research design, the data analysis and the writing of the manuscript. Marcela Ibañez Diaz supervised the research project and provided the funding. I did the field work, conducting the lab-in-the-field experiment in Colombia.

The heterogeneous effects of conflict on education: A spatial analysis in Sub-Saharan Africa
The research project is co-authored with Krisztina Kis-Katos. We both contributed to the conceptualization of the research idea and the research design, the interpretation of the results and the writing of the manuscript. I did the data preparation and analysis. Krisztina Kis-Katos supervised the research project.

Signed: ______________________

Date: ______________________