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GOVERNANCE AND SOCIAL PROTEST IN THE WAKE OF NATURAL DISASTERS

A Spatial Analysis of Social Protests in Central America and the Caribbean

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Abstract

Numerous conflict-studies have explored the link between natural disasters and conflict and have revealed mixed results. In view of this ambiguity, it seems evident that conditions such as the characteristics of the state matter for the occurrence of conflicts in the aftermath of natural disasters. The institutional quality of the state, for instance, is regarded as one of the core moderators of natural disaster induced conflicts. However, the concept of Quality of Government (QoG) remains largely understudied. Based on a new theoretical framework, this thesis proposes that regions with low QoG are more likely to experience social conflicts in the aftermath of natural disasters. The focus will be on social protests that evolve spontaneously and die down quickly as the circumstances of natural disasters mostly do not allow for large-scale mobilization. In that respect, my study differs from existing studies on natural disasters and intrastate or non-state conflicts. By conducting a spatial analysis, I test whether QoG moderates the effect between natural disasters and social protests in seven Central American and three Caribbean countries during the period 2008-2015. For that purpose, I created a new geographically disaggregated data set at the municipality level that allows exploiting the within-variation of the countries. The data set combines various high-frequency geo-referenced data sets on natural hazards with spatial data on social protests from the Social Conflict Analysis Database (SCAD) and with municipality based public opinion data from the AmericasBarometer. The results provide support for the theory that areas with low QoG are associated with more social protests in the wake of natural disasters. Moreover, I find that this is particularly pronounced with respect to the bureaucratic quality of the state. My core findings remain robust across all model specifications and robustness checks.

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I. Introduction

With President Trump's withdrawal from the Paris Climate Accord,[1] the discussion on the security risks of global climate change has reached a new peak. Both politicians and scientists alike appear to be increasingly divided about the causes and socio-economic impacts of global warming and climatic variability. Incidences such as the 2004 Indian Ocean Tsunami have been used to illustrate positive cases where natural disasters have helped to sustain peace in Indonesia (Le Billon & Waizenegger 2007). On the contrary, climate conditions have also been blamed for the outbreak of civil war in Darfur (Ki-moon 2007) and Syria (Kelley et al. 2015). Given that natural disasters will be more frequent and severe in the near future (International Panel on Climate Change 2017), it is of paramount importance to understand the conditions under which climate related natural disasters lead to conflicts.

Existing literature on the disaster-conflict nexus has until now reached little consensus. One group of authors (Brancati 2007, Nel & Righarts 2008, Barron et al. 2009, Eastin 2016, Schleussner et al. 2016, Wood & Wright 2016) suggests a positive effect of natural disasters on conflict. In contrast to that, another group of authors (Bergholt & Lujala 2012, Slettebak 2012) claims that natural disasters are associated with fewer conflicts. In view of this ambiguity, several authors (Raleigh & Urdal 2007, Buhaug et al. 2008, Enia 2009, Goldstone et al. 2010, Raleigh 2010, Omelicheva 2011, Adano et al. 2012, Quiroz Flores & Smith 2013, Detges 2016, Wig & Tollefsen 2016) propose that natural disasters only lead to conflicts under certain conditions. So far, various characteristics of a state have been regarded as crucial by these authors. While the institutional quality of a state has gained much attention from previous literature, the concept of Quality of Government (QoG) remains largely understudied.

Insights from the Managua Earthquake in Nicaragua (1972) suggest that high levels of government corruption and the massive misappropriation of international disaster aid can lead to large-scale rebellions and even regime change (Olson & Gawronsiki 2003). The weak performance of the Nicaraguan government during the natural disaster did not only antagonize the broad public, but also withdrew the support of influential business elites and the church (Olson & Gawronsiki 2003). The Nicaraguan case thus provides good reasons to assume that the QoG influences the link between natural disasters and conflicts. Therefore, this thesis addresses the following research question: "Does QoG prevent social protests in the aftermath of natural disasters?"

[1] President Donald Trump decided on 1st of June 2017 to withdraw the United States from the Paris Climate Accord, an agreement within the United Nations Framework Convention on Climate Change (New York Times 2017).

In order to answer this question, I develop a new theoretical framework based on public choice theory (Ostrom & Ostrom 1977, Chamlee-Wright & Storr 2010) and relative deprivation theory (Gurr 1970) as well as insights from the concept of QoG. My concept of QoG primarily focuses on the de-facto functioning of formal government institutions, but also assumes that high levels of QoG are followed by higher levels of state capacity. More specifically, I argue that regions with a lack of QoG suffer from a discrepancy between citizens' expectations and the performance of the state. This causes feelings of relative deprivation and finally motivates people to protest against the state. Furthermore, I assume that regions with a high level of QoG, are less likely to experience social protests in the aftermath of natural disaster, because the expectation-ability discrepancy does not apply.

My theoretical framework is well adapted to the very specifics of the post-disaster period. First, the focus will be on social protests that evolve spontaneously and die down quickly as the circumstances of natural disasters mostly do not allow for large-scale mobilization. In that respect, my study differs from existing studies on natural disasters and intrastate or non-state conflicts. Second, I use single key features of QoG instead of broad concepts on good governance. Thereby, I make notable efforts to capture the actual source of social grievances that, in the wake of natural disasters, motivate citizens to protest against the government.

In order to assess whether QoG moderates the effect between natural disasters and social protest, I conduct a spatial analysis in seven Central American[2] and three Caribbean countries during the period 2008-2015. For that purpose, I created a new geographically disaggregated data set at the municipality level. The data set combines various high-frequency geo-referenced data sets on natural hazards with spatial data on social conflicts from the Social Conflict Analysis Database (SCAD, Salehyan et al. 2012) and with municipality based public opinion data from the AmericasBarometer (Latin American Public Opinion Project, LAPOP 2004-2016). Moreover, the data set allows me to exploit within-country variation of one of the most disaster-prone regions in the world. Thereby, I address important shortcomings in the disaster-conflict literature.

My results provide modest support for a deterministic relationship between natural disasters and social protests. Most importantly, they reveal that QoG moderates the effect between natural disasters and social protests. I also find that the effect of natural disasters on social protests is particularly pronounced by the quality of the bureaucratic services. The results remain robust across all model specifications and robustness checks. In view of potential biases and limitation of my methodological approach, final interpretation must, certainly, be made with caution. Nevertheless, this study contributes to the ongoing discussion on the security risks of climate change. By highlighting the role

[2] When speaking of Central America, I will also refer to Mexico, even though it officially does not belong to that region.

of QoG in mitigating the negative impact of natural disasters on society, this thesis stimulates the debate on the role of QoG in the natural disaster-conflict nexus. It thereby paves the way for future studies in the field and calls for a re-assessment of existing disaster policies. In addition, this thesis provides important insights for the research field on conflict prevention. Small-scale social protests can, under certain conditions, lead to large-scale rebellions, high levels of violence and even civil war. Hence, by enhancing the QoG in disaster prone areas, social protests will become less likely and thus reduce the risk of long-term conflicts.

The remainder of the paper is organized as follows. The next chapter (sect. II) discusses existing literature on natural disasters and conflicts and positions the research field in a wider context. Thereafter, a theoretical framework is spelled out to address the research question (sect. III). Based on the knowledge we obtain, I deduce two hypotheses. Subsequently, I present the cases and data as well as my methodological approach (sect. IV), before I then turn to the statistical analysis (sect. V). After discussing the main findings of my analysis, I point at potential limitations of my study and provide implications for further research (sect. VI). In the final chapter (sect. VII) I summarize my thesis and formulate initial policy recommendations.

II. Literature Review: Findings and Puzzles

This section provides an overview of the existing literature on natural disasters and conflicts. It is split into four main parts. The first part (sect. 2.2) entails a short introduction into the research field. The succeeding parts (sect. 2.3, 2.4) will present the causal mechanisms and conditioning effects dominating the literature. Finally, existing research gaps and puzzles will be discussed (sect. 2.5). Before I start, for a better understanding I will first pin point the main concepts used in the existing literature and in this thesis (sect. 2.1).

2.1 Clarification of Concepts

Natural Disasters

In the subsequent discussion "natural disaster" will be used as a term for catastrophic events that have their origin in natural hazards. Natural hazards describe geophysical[3] and hydro-meteorological[4] natural phenomena, that bear a damaging potential but do not necessarily lead to natural disasters (WMO

[3] Geophysical natural hazards include: earthquakes and volcanic eruption (Nel & Righarts 2008).
[4] Hydro-meteorological hazards include: droughts, extreme temperature, floods, slides, surges, wild fires and cyclones (Nel & Righarts 2008).

2015). Severe natural hazards, thus, have the potential to disrupt social and economic development, cause property damage, and injure or even kill innocent people, if the human being is exposed to the natural hazard (WMO 2015). In view of global warming, most of the literature discussed below focuses on climate induced natural disasters that result in extreme forms of surges and cyclones, flash floods and severe droughts. In contrast, only few studies (Brancati 2007, Keefer et al. 2011, Carlin et al. 2014, Barone & Mocetti 2014) explore the link between geophysical disasters such as earthquakes or volcanoes and conflict outbreak. The focus of this thesis will be on three different types of natural disasters, which are all linked to climatic variability: 1. droughts, 2. hurricanes and 3. floods.

Social Protests

Further clarification is needed on the terms "social protest" and "conflict". Most of the scientists exploring the link between natural disasters and conflicts, rely on one of the two core conflict categories as suggested by the Uppsala Conflict Data Program (UCDP) and the Peace Research Institute Oslo (PRIO). Therefore, they either focus on any type of "intrastate conflicts", which are defined as "conflicts between the state and a non-state party" (UCDP 2017), but differ in their conflict intensities. Examples include civil conflicts, being also called "armed conflicts", with at least 25 fatalities, and civil wars with over 1000 battle related deaths per calendar year (UCDP 2017). Or they rely on different types of "non-state conflict", which refers to ethnic conflicts (Schleussner et al. 2016) or communal conflicts (Fjelde & von Uexkull 2012), where neither of the two armed groups is represented by the state (UCDP 2017). To be considered as a non-state conflict, the event also must have caused at least 25 battle related deaths (UCDP 2017). In the subsequent literature review, the term "conflict" will be used synonymously to describe both intrastate and non-state conflicts, even though the terms capture two different issues. Both concepts are indicators of political violence and political instabilities. In some cases, they can lead to regime change (Olson & Gawronski 2003).

In the analytical part of my thesis, the focus will be on different types of small-scale and low-violent "social conflicts". As defined by Hendrix & Salehyan (2015, p. 397), social conflicts describe "a broad category that encompasses several forms of contentious collective action, including protests, riots, strikes, and armed attacks that do not meet the conventional criteria of armed conflicts". This definition includes a set of conflicts, which are not in the interest of this thesis and therefore will not be included.[5] More importantly, it entails anti-government actions that do not fulfil the threshold of 25 battle related deaths. This, allows studying localized and small-scale low violent and non-violent events, which is particularly suitable for the context of natural disasters.

[5] This includes: intra-government violence such as coups or disputes within the army, violent repression by state agencies, intra-communal conflicts, and extra-government violence (Salehyan et al. 2012).

For the sake of simplification, the different types of social conflicts, that I chose as suitable for the context of natural disasters, will be termed "social protests" in the rest of the thesis. In the narrow sense, social protests do not belong to the category of political violence. Yet, they indicate political instability and therefore are often pre-cursors of violent conflicts and regime change (Hendrix & Salehyan 2012).

2.2 The Natural Disaster-Conflict Nexus

The first generation of scientists in the research field on natural disasters and conflicts dates back to the 1950s.[6] Political scientists, however, have only become involved as part of the second generation, which evolved at the turn of the millennium, when environmental protection has gained momentum as one of eight core developing goals (UN Millennium Project 2006). Scholars of the second generation have mainly addressed the question of how natural disaster induced conflicts can be resolved (Streich & Mislan 2014). They therefore primarily employed inductive research methods based on single cases studies (ibid.). The third generation, which will be at the core of this literature review, seeks to address substantive theoretical questions by employing multimethod and multilevel approaches. In view of the current trend in data disaggregation in conflict-research,[7] this third generation also comprises a significant number of spatial analyses.

As stated above, some types of natural disasters are caused by climatic variability, thereby, representing extreme forms of environmental change. The literature on natural disasters and conflict, therefore, is embedded in the vast body of literature on environmental change and conflict (Hendrix & Glaser 2007, Raleigh & Urdal 2007, Burke et al. 2009, Buhaug 2010, Brückner & Ciccone 2011, Hendrix & Salehyan 2012, Raleigh & Kniveton 2012, Theisen et al. 2012, von Uexkull et al. 2016). Scientists of the climate-conflict and the natural disaster-conflict nexus alike, primarily use the "resource scarcity argument" to explain the relationship between climate and conflict. It is based on the assumption that environmental change or, more specifically, natural disasters reduce the amount of available resources (Homer-Dixon 1999). Furthermore, this theoretical argument suggests that individuals compete over scarce resources because they need to secure fundamental basic needs such as food, water, or access to medicine (Homer-Dixon 1999). Based on manifold pathways, these authors (Brancati 2007, Nel & Righarts 2008, Barron et al. 2009, Besley & Persson 2011, Eastin 2016, Schleussner et al. 2016, Wood & Wright 2016) claim that resource scarcity provokes conflict.

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[6] The first generation was influenced by theories on „collective action, organizational behaviour and change, social systems, and civil–military relations ", Streich & Mislan (2014, p. 56).

[7] For a discussion see: Gleditsch et al. (2013).

On the contrary, another group of authors (Akcinaroglu et al. 2011, Omelicheva 2011, Bergholt & Lujala 2012, Slettebak 2012) claims that natural disasters are associated with fewer conflicts. Pursuant to them, natural disasters can distract the attention from existing grievances like poor governance and poverty and thereby increase social unity (Slettebak 2012). Other explanations are based on the assumption that the population does not hold the government responsible for their losses because it regards the occurrence of natural disasters as outside the government's control (Bergholt & Lujala 2012). The mixed statistical results obtained by the two different strands of literature can be explained by the use of diverse outcome variables and different data sets and methodological approaches. The following section reviews the most prevalent causal mechanisms used by scholars, who promote a positive relationship between natural disasters and conflict.

2.3 Causal Mechanisms

Change in Migration Patterns

A significant number of authors (Homer-Dixon 1991, Barnett 2003, Reuveny 2007, Brzoska & Fröhlich 2015) explains natural disaster induced conflicts with changing migration patterns. When people have lost their livelihoods through natural disasters, they migrate to non-affected places in search for employment and better access to resources (Reuveny 2007, Black et al. 2011). People thereby can better cope with the socioeconomic effects of the disaster and can protect themselves from further natural disasters. Migration thus functions as a sort of adaption strategy to natural disasters (Adger et al. 2014). Yet, a change in population patterns is also associated with a higher likelihood of conflict (de Sherbinen 1995, see also: Goldstone 2002).

There exist manifold causal channels, through which migration can lead to conflict. First, it is argued that competition over resources increases in the receiving area, when resources are scarce and property rights are not well established (Homer-Dixon 1999, Reuveny 2007). This is particularly the case if migration leads to rapid urbanization and an overrepresentation of interest groups that for instance share the same level of education, occupation or age (Brzoska & Fröhlich 2015). Second, if integration of migrants fails, rebel groups might use this outlet for recruiting frustrated people (Homer-Dixon 1999, Reuveny 2007). And third, distrust between the migrant receiving community and the migrant sending community might also cause conflict (Reuveny 2007).

Even though migration appears to be a prominent explanation for the occurrence of natural disaster related conflicts, empirical evidence is scarce. Still, a few quantitative studies at the national level (Barrios et al. 2006, Drabo & Mbaye 2014) and some at the sub-national level (Raleigh & Urdal 2007, Bhavnani & Lacina 2015, De Juan 2015, Khan et al. 2015, Baez et al. 2016, Bohra-Mishra et al. 2016) are worth noticing. Baez et al. (2016) find evidence that different types of natural disasters increase youth migration in Central America and the Caribbean. Moreover, Bohra-Mishra et al. (2016) gain support for their hypothesis that climate change and to a small extent also natural disasters augments out-migration in the Philippines. In addition, Khan et al. (2015) find that out-migration increases among certain groups of society in Bangladesh. Accordingly, farmers are more likely to migrate than business men, in the wake of natural disasters. Lastly, De Juan (2015), contributes by studying geographical patterns on the role of migration in Darfur. By using a mixed-method approach, he first provides qualitative evidence for the association between migration and intercommunal conflicts. In a quantitative approach, he then tests whether climate change, captured by satellite data on long term vegetation change increases the level of violence in specific villages.

Polarization

Another widely shared belief is that cleavages along different ethnic or political lines can trigger conflicts after natural disasters (Homer-Dixon 1999, Raleigh 2010, Fjelde & von Uexkull 2012, Theissen et al. 2012, Eastin et al. 2016, Schleussner et al. 2016, von Uexkull et al. 2016).[8] The first explanation based on ethnic polarization builds on the migration literature (e.g. Reuveny 2007). It suggests that natural disaster induced migration can change the ethnic or political constellation of the population (Reuveny 2007). This leads to a change in the balance of power between existing ethnic groups and may polarize society (ibid.). The second ethnicity-based theoretical argument contends that natural disaster induced conflicts are particularly likely if ethnic cleavages are pre-existing in society (Raleigh 2010, Fjelde & von Uexkull 2012, von Uexkull et al. 2016). It regards selective good provision along the ethnic lines as the cause of natural disaster induced conflicts (ibid.). Accordingly, some ethnic groups are part of the winning coalition[9] and therefore have better access to resources and are more likely to live in areas with sufficient infrastructure (von Uexkull et al. 2016). Consequently, the winning coalition is less vulnerable to natural disasters and less likely to lose their livelihoods, which can lead to conflicts between different ethnic groups (von Uexkull et al. 2016).

Recently, authors (Eastin 2016, von Uexkull et al. 2016, Schleussner et al. 2016) have provided statistical evidence for the causal chain on natural disasters, ethnic polarization and conflicts. Von Uexkull et al. (2016), for instance, use spatial settlement data in combination with remote sensing data

[8] The role of ethnicity in conflicts has been debated in the civil war literature (Fearon & Laitin 2003, Collier & Hoeffler 2004). It finally has been proven to be crucial (Montalvo & Reynal-Querol 2005, Esteban & Schneider 2008).

[9] According to selectorate theory (Bueno de Mesquita et al. 2003), the "winning coalition" is defined by the set of people that leaders acquire to stay in power, whereas the "selectorate" refers to the people who can choose the leader. It is assumed that the size of the two components varies between different regime types (ibid.).

on the use of agricultural land at group level to explore the vulnerability of different ethnic and agricultural groups in Africa and Asia. Their findings reveal that droughts increase the likelihood of civil conflicts by agriculture dependent and marginalized groups (von Uexkull et al. 2016). Schleussner et al. (2016) also test the ethnic polarization argument by conducting an event coincidence analysis at the cross-country level. In line with Schleussner et al. (2016), Eastin (2016) finds that natural disasters caused by climate variability only increase the likelihood of conflict if ethnic fractionalization is high.

Impact on State Capacity

Another strand of literature (Homer-Dixon 2001, Kahl 2006, Raleigh & Urdal 2007, Eastin 2016, Wood & Wright 2016) relies on state-centric approaches. These authors contend that natural disasters reduce state capacity in a variety of direct and indirect ways and thereby lead to conflict. First, natural disasters can reduce the ability of the government to suppress or prevent insurgency and thereby provoke conflict (Kahl 2006, Eastin 2016). Hence, when resources are primarily used for disaster relief and reconstruction projects, the state lacks financial and personnel resources for counterinsurgency campaigns (Kahl 2006, Quiroz Flores & Smith 2013, Eastin 2016). Second, it is argued that natural disasters can decrease the level of state penetration when infrastructure is damaged (Eastin 2016). On the one hand the reduced level of state reach increases the mobilization ability of insurgent groups and thereby turns conflict more likely (ibid.). Yet, on the other hand, it can also hamper the provision of disaster relief when state agencies such as the military are unable to reach affected regions (ibid.). The reduced coping capacity of the state then increases the likelihood of anti-state campaigns (Eastin 2016, Wright 2016). By using state repression as an indicator of reduced state capacity, Wood & Wright (2016), provide evidence that natural disasters reduce state capacity. Likewise, by conducting an event-history analysis, Eastin (2016) finds that natural disasters prolong conflicts because of the reduced counterinsurgency capacity of the state.

2.4 Conditioning Effects

This section outlines the conditioning effects prevalent in the literature. According to a significant number of authors (Goldstone et al. 2010, Raleigh & Urdal 2007, Buhaug et al. 2008, Enia 2009, Raleigh 2010, Omelicheva 2011, Adano et al. 2012, Quiroz Flores & Smith 2013, Detges 2016, Wig & Tollefsen 2016) natural disasters only lead to conflict under certain conditions. Thus, these authors do not propose a deterministic relationship between natural disasters and conflicts. Instead they assume a conditional relationship that is determined by the vulnerability of the state. In the words of Sjöstedt & Povitkina (2016, p. 4), vulnerability describes "society's ability and capacity to cope with disturbances and moderate the outcome to ensure benign or only small-scale negative consequences" (see also:

Manyena 2006). Vulnerability is, thus, determined by various economic and political factors that shape government's decision to invest in disaster prevention and increase disaster preparedness (Wisner 2004, see also: Raleigh & Urdal 2007).

Economic Development

Based on the civil war literature (Fearon & Laitin 2003), these authors (Raleigh & Urdal 2007, Brancati 2007, see also: Homer-Dixon 1999) claim that conflict risk depends on the economic development of the state. Subsequently, poor and less developed states do not have the capability to invest in preventive mechanisms and provide sufficient disaster relief, which turns conflict more likely (Brancati 2007, Raleigh & Urdal 2007). In order to test this claim, Raleigh & Urdal (2007) create a sub-sample of low- and high-income states. Their findings reveal, that the economic development, as measured by GDPpc, decreases conflict risk in low-income states but not in rich countries (Raleigh & Urdal 2007). Brancati (2007) provides first evidence for a moderating effect of GDPpc on the statistical link between natural disasters and conflict.

Regime Type

Other authors regard regime type as the major determinant of conflict vulnerability (Omelicheva 2011, Quiroz Flores & Smith 2013). Accordingly, certain regime types are either less interested in the provision of public goods or unable to adopt the needed coping mechanism because of weak decision-making capabilities. Autocracies, for instance, are argued to be less concerned about disaster policies because their constituency is not based on the broad support of the civil society (Quiroz Flores & Smith 2013). Whether natural disasters also increase the likelihood of conflict in autocracies is a debated issue. According to Omelicheva (2011), autocracies are the least likely to experience conflict as a consequence of natural disasters because they are not contested by civil society. In contrast, Quiroz Flores & Smith (2013) find that natural disasters increase the likelihood of anti-state protest in autocracies. They contend that natural disasters facilitate the coordination of protest movements, particularly in urban areas (Quiroz Flores & Smith 2013). In addition to that, empirical evidence (Omelicheva 2011, Marks & Lebel 2016) has shown that factional countries are associated with a higher conflict risk after natural disasters. Hence, they are characterized by polarized and weak governance and therefore are less likely to adopt disaster policies (Omelicheva 2011, see also: Goldstone 2010). Moreover, factional countries lack pluralism and cohesion and therefore are more likely to face contestation (ibid.).

Institutions

Lastly, an increasing number of authors (Goldstone 2010, Raleigh 2007, Buhaug et al. 2008, Enia 2009, Omelicheva 2011, Adano et al. 2012, Detges 2016, Wig & Tollefsen 2016) contends that a weak institutional setting can trigger conflict after natural disasters. This argument is closely linked to the argument on "regime type" because some regime types (transitional and factional countries) are characterized by weak institutions. If the institutional setting, for instance, does not provide any conflict resolution mechanisms, conflict after natural disasters becomes more likely (Omelicheva, 2011, Wig & Tollefsen 2016). Moreover, conflict arises if the institutional arrangement does not guarantee a fair provision of public goods to all citizens. Accordingly, weak or "grabber-friendly" institutions do not distribute power and influence evenly, but allow few politicians and influential leaders to exert control over resource revenues, which turns conflict more likely (Adano et al. 2012, p. 67). This applies particularly to resource abundant states, but can also be caused by the influx of international disaster aid (Enia 2009). Empirical evidence on the role of institutions in the disaster-conflict nexus is scarce. For instance, Omelicheva (2011) provides evidence that political and economic state-led discrimination as measured by the Minority at Risk Project (MAR, CIDCM 2009), significantly increases conflict risk after natural disasters. Furthermore, Detges (2016) finds that access to key infrastructure such as roads or water moderates the effect between natural disasters and conflict.

2.5 Research Gaps

The above discussed body of literature has made important contributions to the understanding of the natural disaster-conflict nexus, but remains incomplete in several ways. First, statistical evidence for the link between natural disasters and conflict is ambiguous, which turns a deterministic relationship unlikely. Instead, it points to a conditional effect between natural disasters and conflicts. Recently, more nuanced theoretical approaches have been developed, incorporating various intervening factors that are related to the characteristics of the state. Numerous scholars have emphasized the importance of institutional factors as intervening and conditioning variables, but have failed to sufficiently test their arguments. For instance, by using the MAR data set (CIDCM 2009) Omelicheva (2011) only captures the discrimination of a small part of the population, but does not estimate the overall level of selective good provision by the state.[10] With my quantitative approach, I seek to establish a coherent link between my theoretical concept and statistical analysis and thereby address existing weaknesses in the literature.

[10] In order to be considered in the MAR data set (CIDCM 2009), ethno-political and non-state communal groups must be politically active. Moreover, it does not consider majority groups that are deprived in minority-rule regimes.

Second, scientists who emphasize the role of institutional quality have largely neglected concepts such as "good governance" (e.g. Kaufmann et al. 2009) or "Quality of Government" (Rothstein & Teorell 2008). Yet, both the de-jure and the de-facto functioning of institutions are particularly driven by aspects such as bureaucratic quality, rule of law and the level of corruption (Rothstein & Teorell 2008). Therefore, there is an obvious need for further theoretical conceptualization. In addition to that, most of the conflict theories tend to focus on simple grievance factors such as poverty or inequality, whereas poor quality of government might better reflect the relative deprivation theory (Hegre & Nygård 2015). By developing a new theoretical framework that links natural disasters, quality of government, and social protests, and I seek to fill these gaps.

Third, most of the concepts used to define natural disaster induced conflicts do not account for the specific circumstances of natural disasters. By using violent intrastate and non-state conflicts as outcome variables, most of the scientists do not consider that both the mobilization and military capabilities might be reduced in the aftermath of natural disasters (Hendrix & Salehyan 2012). Large scale rebellions and mass mobilization require long-term planning, financial resources and leadership — prerequisites that are particularly not given when resources are reduced as a consequence of natural disasters (Hendrix & Salehyan 2012). By focusing on small-scale incidences of "social conflict", this study seeks to adjust the concept of conflicts to the specifics of the post-disaster period and thereby addresses existing shortcomings in the literature.

Fourth, standard country-year-level or between-country comparisons used in the literature are often too broad to capture the spatial and temporal dimensions of natural disasters and conflicts. The over-aggregation of data blends important within-country variation. Usually, natural disasters affect a certain part of the population, whereas the rest of the country is not directly affected. In addition, the quality of government does not only vary across but also within countries (Charron & Lapuente 2013). To capture this within-country variation, a more disaggregated unit of analysis is needed. The over-aggregation of the data also prevents us from studying certain geographic covariates that predict the occurrence of conflicts. The level of state reach, for instance, represents an important predictor of conflict (Weidmann et al. 2010), which can be measured at the sub-nation level but hardly can be controlled for in cross-country analyses. Social protests constitute particular localized events that occur in close proximity to the natural disaster (Hendrix & Salehyan 2012). Exploring the impact of natural disasters on social protests, therefore requires data with a fine spatial resolution. By creating a new geo-referenced data set at the municipality level, this study faces the need for further data disaggregation. Moreover, by exploring the within-country variation this study overcomes existing weaknesses in the literature.

Lastly, by focusing on Central American and the Caribbean, this thesis covers a disaster-prone region that has been largely understudied by the existing literature. Most of the quantitative country-level analyses have a global scope (Brancati 2007, Nel & Righarts 2008, Bergholt & Lujala 2012, Slettebak 2012, Almer et al. 2014, Schleussner et al. 2016), whereas disaggregated analyses primarily focus on Africa (Theisen et al. 2012, Detges 2016, von Uexkull et al. 2016) and Asia (Khan et al. 2015, Bohra-Mishra et al. 2016, von Uexkull et al. 2016). Yet, not a single study investigates the link between natural disasters and social conflicts in Central America and the Caribbean.[11]

III. Theory on Natural Disasters, Quality of Government and Social Protest

In the following, a theoretical framework will be presented to describe under which conditions natural disasters provoke social protest. Insights from public choice theory (Ostrom & Ostrom 1977, Chamlee-Wright & Storr 2010) and relative deprivation theory (Gurr 1970), as well as the concept of Quality of Government (Rothstein & Teorell 2008) will be used for the development of the argument. The theoretical argument will have global application and not be restricted to single regions or countries with a certain regime type or economic status.

In line with Raschky (2008) and Ahlbom & Povitkina (2016), my theory builds on the assumption that the ruling government has the power, to protect its citizens from natural disasters by providing public goods. According to public choice theory (Ostrom & Ostrom 1977), pure public goods are neither excludable nor rivalrous and therefore should be distributed equally among the population. In practice, however, access to public goods is often unevenly distributed, in particular, if society is characterized by nepotism and favouritism (Raschky 2008). Even though public choice theory often does not apply in practical terms, it is still useful to explain why people engage in collective action in the aftermath of natural disasters.

The second assumption used for my theory stipulates that different governments vary in their capacity and willingness to provide public goods in the wake of natural disasters. The steadily growing research field on topics such as "good governance" addresses this variation across different forms of governance. Most of existing concepts on "good governance" suffer from weak theoretical conceptualizations (Rothstein & Teorell 2008). They are often broad in nature and not seldom based on highly aggregated measures such as the World-Wide Governance Indicators, provided by the World Bank (Kaufmann et al. 2009). In order to describe the role of "good governance" in the wake of natural

[11] In their sub-national analysis Baez et al. (2016) study the association between natural disasters and migration in Central America and the Caribbean, but do not link it to conflict. In addition, several single-case studies explore the relationship between natural disasters and social accountability in Latin America (Carlin et al. 2014, Remmer 2014, Katz & Levin 2016, Stoyan et al. 2016)

disasters, I will rely on the concept of Quality of Government (QoG). Rothstein & Teorell (2008), define QoG as impartiality, which is often simply described as the opposite of corruption (Rothstein 2014). The authors define impartiality as "an attribute of the actions taken by judges, civil servants, politicians, and the like" (Rothstein & Teorell 2008, p. 170). The concept of QoG thus focuses on the output side of the political system and highlights the importance of the de-facto functioning of formal government institutions (Rothstein & Teorell 2008).

The concept of QoG is often operationalized as impartial acts of government. According to the QoG Standard Data set (Teorell et al. 2017, p. 4), QOG comprises "trustworthy, reliable, impartial, uncorrupted, and competent government institutions". More precisely, they include variables related to impartiality, bureaucratic quality, and corruption, as well as rule of law and transparency (Teorell et al. 2017). The measurement of the concept, is thus limited to a few key features. In that respect, it differs significantly from existing multifaceted concepts of "good governance" that also consider aspects such as the level of democracy, efficient market policies, political stability and other positive socio-economic variables in their definitions. It herby is important to note that the concept of QoG does not neglect these aspects, but proposes them as a logical consequence of QoG (Rothstein & Teorell 2008). In a narrow sense, the concept of QoG, therefore, does not cover the capacity to provide public goods in the wake of natural disasters. Yet, it still can be assumed that a government with a high level of QoG also has an increased level of state capacity that facilitates the provision of public goods (Rothstein & Teorell 2008).

In consequence, a government with a high level of QoG should be able and willing to adopt and implement policies that secure the provision of public goods. When applied to the special situation of natural disasters, the provision of public goods should cover both the pre-disaster and the post-disaster period (Congleton 2006, Raschky 2008). In particular, it should involve the adoption of disaster prevention mechanisms in the form of early-warning systems, and evacuation programs (Raschky 2008). Furthermore, it should entail investments in infrastructure projects and education programs in order to reduce the disaster vulnerability of a region (Raschky 2008). Lastly, a government with a high level of QoG, should be able and willing to provide disaster relief aid and reconstruction projects in the aftermath of natural disaster (Raschky 2008). In contrast, governments characterized by low bureaucratic capacity, a weak rule of law, and corruption, will be unlikely to adopt these policies. Instead, they will be characterized by ineffective distribution of public goods and a lack of preventive measures (see also: Raschky 2008, Ahlbom & Povitkina 2016).

The third assumption underpinning my theoretical framework is closely linked to my first assumption. It argues that collective actions are based on citizens' expectations on the role of the government.

According to Chamlee-Wright & Storr (2010), citizens' expectations can be shaped by existing norms and formal rules, but also by personal characteristics of the citizens. Furthermore, citizens' past experience with natural disasters can influence the expectations of citizens (Sloane 1991, Miller & Listhaug 1999). Subsequently, citizens that have experienced natural disasters in the past, might expect the government to learn from previous mistakes (ibid.). In addition, people living in developing nations, might have different expectations on their government than people living in developed nations (Manning 2001). [12]

Chamlee-Wright & Storr (2010), provide a framework for public choice theory that allows to link citizens' expectations to individual strategies. Accordingly, citizens have expectations about "what the government intends to do and about what the government is capable of doing" (Chamlee-Wright & Storr 2010, p. 256). Depending on either pessimistic or optimistic attitudes towards the performance of the government, citizens then decide between self-help strategies, tentative strategies or mixed strategies that may result in acts of contestation (Chamlee-Wright & Storr 2010). "Optimistic" means that the individual is convinced that the government will effectively provide goods and services, whereas "pessimistic" means that the individual believes that the government will fail to do so. Tentative strategies are mostly chosen if the individual is optimistic about both the intentions and capabilities of the government (ibid.). This type of individuals is also labelled "naively optimistic", because these individuals blindly trust the government in providing public provision and services in the wake of natural disasters (Chamlee-Wright & Storr 2010).

In contrast, individuals who are pessimistic about the intentions and capabilities of the government follow self-help strategies or mixed strategies (ibid.). Self-help strategies include, for instance, the own rebuilding of damaged buildings or the migration to other less affected areas (ibid.). Yet, in most of the cases, the authors argue, self-help strategies are adopted in combination with activities that aim to increase the performance of the government (ibid.). These mixed strategies, cover both self-help strategies and political activism in the form of demonstrations, political protests and attendance in local community meetings (Chamlee-Wright & Storr 2010).

In contrast to authors such as Achen & Bartels (2004) or Caplan (2007), I do not assume that citizens are irrational actors. Therefore, I also argue that citizens do not blame the government for the event itself but for the weak performance before, during and in the aftermath of the event. It herby is important to note, that I expect citizens to protest if they are deprived from public goods, as well as if

[12] It is beyond the scope of this thesis to empirically assess, whether citizens who are not accustomed to the provision of public goods are also less likely to expect public goods in the wake of natural disasters. Therefore, this train of thought will here not be further specified from a theoretical perspective.

they receive aid, but perceive it as unevenly distributed. This is because partial public good provision is argued to reduce the amount of public goods distributed to the people (see also: Raschky 2008). Consequently, citizens receive less public goods than available. Based on the grievance-mechanism (Gurr 1970), I argue that if the government proofs unable to meet citizens' expectations on government performance, this may open political space for contestation. The relative deprivation theory (Gurr 1970) contends that citizens protest, because they lose social trust in authorities and feel sentiments of relative deprivation when the expectation-ability discrepancy exceeds a certain tolerance level (see also: Davies 1962).

Being rational actors, one should assume that citizens weigh the cost and benefits to overcome collective action problems (Olson 1965). Yet, guided by their emotions (Gurr 1970), I expect social protest to occur rather spontaneously as a way to express frustration and raise attention to their perceived deprivation. Furthermore, I expect the citizens' ability to mobilize and militarize to be reduced after the natural disaster because of the socio-economic damage caused by the disaster (see also: Hendrix & Salehyan 2012). Therefore, I expect to observe small-scale incidences of social unrest as a consequence of natural disasters. Whether the social protest turns violent or not depends on country specific factors. Thus, I assume that social protest in countries from the Violent Northern Triangle[13] or Mexico, for instance, are more likely to turn violent because people are more used to the exposure to violence. In such regions, groups with pre-established motives unrelated to the disaster might seize their opportunity and join the social conflict (Nel & Righarts 2008). Finally, it is important to note, that I do not expect the outcome to be negative per se. Hence, social protest can also lead to policy change, contestations or even regime change.

In sum, I argue that municipalities with a low quality of government are particularly vulnerable to natural disasters because the government has both low state capacity and low intentions to cope with the disaster. The combination of rising social grievances and loss of trust in the government finally motivates people to protest against the state. QoG therefore is not only expected to ensure the provision of public goods but also to prevent the occurrence of social protest. Thus, the following hypotheses can be deduced:

H1: Natural disasters increase the likelihood of social protest.

H2: Quality of Government moderates the effect between natural disasters and social protest.

[13] According to the Council on Foreign Relations (2017) El Salvador, Guatemala and Honduras are one of the world's most violent countries and therefore labeled Violent Northern Triangle of Central America.

IV. Research Design

In the first chapter of this section I will introduce the cases and time frame under study. Subsequently, I will present the data used to conduct the empirical analysis (sect. 4.2) and explain the operationalization of the core variables (sect. 4.3). Descriptive statistics and graphs will provide an impression of the distribution of the data (sect. 4.4). In the last chapter (sect. 4.5), the method used to conduct the statistical analysis will be described.

4.1 Cases and Timeframe

My analysis focuses on Central America and the Caribbean. This region is particular worth studying because it is extremely vulnerable to natural hazards (Bashir et al. 2012).[14] Several climatic phenomena, such as the El Niño Southern Oscillation (ENSO) cycle or the hurricane belt, significantly affect the weather conditions in the region (European Commission 2017).[15] In consequence, the region suffers from severe droughts, flash floods, and extreme hurricanes (European Commission 2017). Due to climate change, the number of natural hazards in Central America and the Caribbean is expected to significantly increase in the upcoming years (Baez et al. 2016). Being surrounded by several tectonic plates, the region is also vulnerable to geophysical natural hazards, such as earthquakes or volcanic eruptions. However, in view of the increase in natural hazards caused by global climate change, I decided to focus solely on meteor-hydrological climatic shocks such as 1. droughts, 2. hurricanes and 3. floods and exclude geophysical hazards.

The region also provides a sufficient variation in the level of QoG and therefore supplies good data to assess my second hypothesis. Hence, there is evidence that the QoG varies significantly between and within Latin American countries (Weiss Fagen 2008, Luna & Soifer 2015). Moreover, the region I have chosen primarily represents young democracies or transition countries and therefore is particularly under stress test when facing natural disasters (Omelicheva 2011, Ahlbom & Povitkina 2016). According to the Polity IV data (Marshall & Jaggers, 2004-2014), the democracy levels of the countries under study range from "open anocracy" (Haiti) to "democracy" (Dominican Republic, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Nicaragua, Panama) and "consolidated democracy" (Costa Rica).

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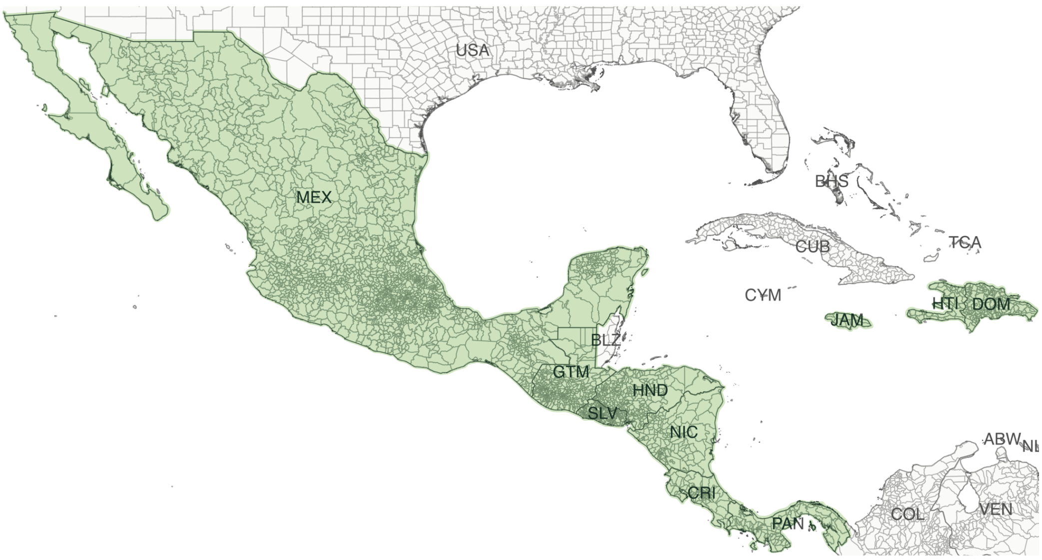
[14] It is reasonable to ask, why I did not include South America in my analysis, as it resembles my region of interest in geographical and political terms. This is mainly because the SCAD (Salehyan et al. 2012) does not cover South America.

[15] The ENSO cycle describes "naturally occurring phenomena that result from interactions between the ocean surface and the atmosphere over the tropical Pacific." (NOAA 2012). It mainly results in severe droughts and flash floods, but also affects the occurrence of hurricanes (ibid.).

My unit of analysis will be the municipality-year because it is the smallest geographic unit covered by the core data sets. The size of the unit is reasonable for studying social protests in the aftermath of natural disasters because social protests are expected to occur in close proximity to the disaster, but not necessarily at the area where the damage occurred. My main sample consists of 3289 municipalities[16] in seven Central American (Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama) and three Caribbean countries (Dominican Republic, Haiti, Jamaica). The SCAD (Salehyan et al. 2012) only provides data for countries with a population size of at least one million inhabitants. For that reason, Belize and nine small-island states in the Caribbean dropped out of my sample. The sample size is further restricted by the AmericasBarometer (LAPOP 2004-2014), that does not contain public opinion information on Cuba. The study period is also determined by the data availability of the core data sets ranging from 2008 until 2015. All these aspects result in 26.312 municipality-year observations. Furthermore, I created a subsample of the data by restricting the cases to those municipalities, where QoG was available. This reduced the number of municipality-year observations to 4.214. Moreover, the number of municipality under study then differs slightly from year to year.[17]

MAP 1: Administrative Boundaries for Central American and the Caribbean



[16] The 13 regions in Jamaica are treated as municipalities because GAUL (EC-FAO Food Security Programme 2008) does not provide second order administrative units for that particular country.
[17] The number of municipalities under study ranges from 474 (2012-2013) to 581(2008-2009) municipalities per year.

4.2 Data

The data sets described in this section are characterized by different geographic units. In order to obtain information referring to the same geographic level, I overlaid the individual geographic units with global administrative units from Global Administrative Unit Layers (GAUL, EC-FAO Food Security Programme 2008). GAUL (EC-FAO Food Security Programme 2008) provide best available information on global administrative boundaries at country, first (province), and second (districts) order level.[18] I will use the second order administrative boundary names for Central America and the Caribbean because, with the exception of Jamaica, they correspond to the municipalities provided in the AmericasBarometer (LAPOP 2004-2014). For Jamaica, I will use first order administrative boundaries in order to identify the location of the different provinces.

Social Protest Data

To capture the occurrence of *social protest,* I will use geo-referenced data from the Social Conflict Analysis Database (SCAD, Salehyan et al. 2012). The SCAD (Salehyan et al. 2012) entails information on localized nonviolent and low violent conflict events such as organized and spontaneous demonstrations, riots and strikes and other incidences of social conflicts that are often overlooked by conventional conflict databases. The data is particularly suitable for my analysis because it covers small scale localized conflict events that are more likely to erupt as a response to natural disasters than large-scale conflicts.[19] It includes all countries in Africa, Central America and the Caribbean with a minimum of one million inhabitants and covers the period between 1990 and 2015 (ibid.). Importantly, the data excludes all violent events that are associated with existing civil conflicts in the countries.[20] This reduces the likelihood of establishing spurious correlations based on other sources of conflict. Another reason, why the SCAD (Salehyan et al. 2012) is suitable for assessing the link between natural disasters and conflict is its spatial disaggregation. The geographic unit provided by the data is at point level. By collapsing the number of social protests per municipality, I obtain information on the level of social protest at municipality level.

The information provided by the SCAD (Salehyan et al. 2012) is based on newswires from Associated Press and Agence France Presse. Therefore, the data might suffer from an over-reporting in urban areas and an underreporting in rural areas (Hendrix & Salehyan 2015). Hence, international reporters

[18] For some individual cases, GAUL (EC-FAO Food Security Programme 2008) also provides global administrative boundaries at third, fourth or fifth level.

[19] I chose not to use the widely used UCDP Georeferenced Event Data (GED, Sundberg & Melander 2013) because it only includes lethal events that must have caused at least 25 fatalities. The UCDP GED records some single lethal events for violent prone countries such as Mexico or El Salvador. Yet, UCDP GED does not provide information on lethal events in any other Central American and Caribbean countries.

[20] The SCAD (Salehyan et al. 2012) excludes all violent events which are listed as civil conflicts in the Uppsala Armed Conflict Database.

are often based in major cities, and they may be unaware of or unwilling to cover social conflicts that occur in remote areas. In view of their relatively small country size, this reporting bias might not apply to the Caribbean Countries (Haiti, Dominican Republic, Jamaica). In contrast, the reporting bias could apply to larger countries, such as Mexico or Guatemala, that are characterized by poor infrastructure (IMF Diálogo a fondo 2017) and therefore are less likely to be reached by international reporters. In principle, the SCAD (Hendrix & Saleyan 2012) is considered to be less biased for the Central American and Caribbean than for the African region (Hendrix & Salehyan 2015). This is explained by the fact that the Western hemisphere, and the U.S. in particular, is more interested in political issues of the Central American and Caribbean region and less focused on the African context.

Flood Data

First, I will use data from the Dartmouth Flood Observatory (DFO) Archive (Brakenridge 1985-2017), which provides comprehensive data on large-scale floods for the period from 1985 until the present. In order to be considered in the DFO Archive (ibid.), the flood must have caused fatalities or significant damage to infrastructure and agriculture. Besides rainfall induced river floods, the data also includes other types of floods such as coastal floods that arise from cyclones and storms, and floods that are caused by dam breaks and snowmelt.[21] In that respect, the DFO Archive (ibid.) provides as much more comprehensive collection of floods than the widely used EM-DAT database by the Centre for Research on the Epidemiology of Disaster (CRED).

Similar to the EM-DAT database (CRED), the DFO Archive (Brakenridge 1985-2017) includes information, such as the start and end dates of a flood event and the severity and kind of damages caused by the floods. Yet, in contrast to the EM-DAT database, the DFO Archive (ibid.) also contains the estimated area effected by the flood, as well as its centroid. It is important to note that the size of the polygon representing the affected flood area might slightly differ from the actual area of inundation (ibid.). To identify the municipality in which the floods occurs, I will use the polygon-centroids provided by the flood data and aggregate the data at municipality-level by calculating mean values per year and municipality.[22] Lastly, one should also be aware of the fact that the information by the DFO Archive (ibid.) is obtained through news and governmental, instrumental, and remote sensing sources. As a consequence, the reporting of floods might be biased because of varying levels of news coverage in the different countries and regions. Despite of potential biases in the data, I will use the DFO

[21] I decided against using the ERA-Interim dataset used by Flatø & Kotsadam (2014) to measure the occurrence of floods and droughts because it only captures one single type of floods (rain fall induced floods) and in terms of droughts it also does not account for the level of evaporation.

[22] In order to maintain the temporal variation of the SPEI data, I aggregated the flood data per year (2008-2015) and compiled each file afterwards using STATA.

Archive (Brakenridge 1985-2017) since it represents the most comprehensive disaggregated and publicly available data source on large scale floods.

Drought Data

Second, I will use the Standardized Precipitation-Evatransporation Index (SPEI, Vicente-Serrano et al. 2010) which is a multi-scalar drought index based on global population-weighted monthly rainfall and temperature data from the Climatic Research Unit (CRU) of University of East Anglia. The SPEI data has a spatial resolution of 0.5 ° grids and covers the period between 1901 and 2014. Each SPEI value expresses the standard deviation from the long-run averages per grid cell and month. Accordingly, positive SPEI values define an above average water balance, whereas negative SPEI values characterize a below average water balance in the grid cell. As defined by the literature, a severe drought assumes a SPEI value of -1.5, whereas an extreme drought exceeds a SPEI value of -2.5 (Tollefsen et al. 2012). The estimation technique of the SPEI is based on Penman-Montheith estimation, which is superior to Thornthwaite[23] estimation techniques (Thornthwaite 1948). Accordingly, Penman-Montheith does not only consider temperature and precipitation data but also entails wind speed, relative humidity and solar radiation (Beguería et al. 2013).

In addition, the SPEI addresses several weaknesses of conventional drought indicators, such as the Palmer Drought Severity Index (PDSI, Palmer 1965) or the Standardized Precipitation Index (SPI, McKee et al. 1993). First, the SPEI allows the identification of different types of droughts. Second, it allows exploring droughts in relation to different hydrological systems. Even though this study does not distinguish between different types of droughts, the SPEI will be used for this analysis. By taking all the above-mentioned criteria into consideration, the SPEI constitutes the most complete and statistically robust drought index, which is also easy to calculate and interpret. In order to assign the drought data at grid level to each municipality and year, I overlaid the grid data with administrative units from GAUL (EC-FAO Food Security Programme 2008) by calculating mean values per year and municipality.[24]

Hurricane Data

For hurricanes, I will use data from the Global Risk Data Platform (UNEP-Grid Geneva 2015) which provides information on the location and time of severe hurricanes. The data from the Global Risk Data Platform (UNEP-Grid Geneva 2015) represents a modified version of the International Best

[23] The Thornthwaite Monthly Water Balance model (Thornthwaite 1948) uses temperature and precipitation data to model “soil moisture storage, snow storage, surplus, and runoff” (USGS 2017).

[24] In order to maintain the temporal variation of the SPEI data, I aggregated the drought data per year (2008-2014) using QGis version 2.18.7(Quantum Gis Development Team 2009) and then compiled each file afterwards using STATA.

Track Archive for Climate Stewardship (IBTrACS) hurricane database by the National Oceanic and Atmospheric Administration (NOAA 2015). In order to be considered as a hurricane by the Global Risk Data platform (UNEP-Grid Geneva 2015), hurricanes must meet the category 5 of the Saffir-Simpson Hurricane Wind Scale.[25] A hurricane of category 5 has a minimum wind speed of 252 km/h and has the potential to massively destroy infrastructure and housing. In other words, category 5 hurricanes are likely to turn most of the area uninhabitable for several weeks or even months (NOAA 2017). In contrast to IBTrACs raw data (NOAA 2015), the Global Risk Data Platform (UNEP-Grid Geneva 2015) also takes the movement of the hurricanes through time into consideration. Consequently, the Global Risk Data Platform (UNEP-Grid Geneva 2015) does not use points and lines for the geo-location of hurricanes, but provides data at polygon level, which makes the data particularly suitable for my analysis. To identify the municipality in which each hurricane occurs, I overlaid the hurricane polygons from UNEP-Grid Geneva (2015) with global administrative units from GAUL (EC-FAO Food Security Programme 2008) and aggregated the data at second-order administrative level by calculating mean values per year and municipality.[26]

Quality of Government Data

I will use data from the AmericasBarometer (LAPOP 2004-2016) to capture the *Quality of Government* at municipality level. The AmericasBarometer (ibid.) provides public survey data for 34 countries in the Western Hemisphere. Each country survey of the AmericasBarometer (ibid.) is implemented based on a national probability design that accounts for the stratification of the data. Moreover, every survey wave is weighted to 1.500 survey respondents per country allowing cross-country analyses (ibid.) The more recent survey waves (2012, 2014) of the AmericasBarometer Grand Merge Dataset (LAPOP 2004-2014) are representative at the municipality level, whereas older waves (2004-2008) are only stratified by province and urban or rural area. Survey participants are voting-age adults and interviewed face to face in their households. Some survey items are provided for all survey waves (e.g. bureaucratic quality, level of corruption and rule of law), whereas other items (e.g. quality of infrastructure) are only included in recent waves.

The geo-coding of the municipalities in the AmericasBarometer (LAPOP 2004-2016) required a time-consuming procedure. The more recent waves (2012, 2014) of the AmericasBarometer Grand Merge Dataset (LAPOP 2004-2014) include full information on the municipality name. In contrast, some municipality entries of the older waves (2008, 2010) only contain single municipality numbers. Therefore, I assigned the municipality names from the national surveys (2008, 2010) to the municipality

[25] The Saffir-Simpson Hurricane Wind Scale categorizes hurricanes based on wind speed from one to five (NOAA 2017).

[26] In order to maintain the temporal variation of the hurricane data, I aggregated the hurricane data for each year (2008-2015) using QGis and then compiled each file afterwards using STATA.

numbers in the Grand Merge Dataset (LAPOP 2004-2016) by using the identification and year variable. Furthermore, to identify the geographic location of the municipalities in the AmericasBarometer (LAPOP 2008-2014), I assigned each survey municipality to administrative boundaries from GAUL (EC-FAO Food Security Programme 2008). In order to be able to merge the administrative polygons at second (and first) administrative level with the AmericasBarometer (LAPOP 2008-2014), I adjusted on a case by case basis all municipality names from the AmericasBarometer to the municipality names from GAUL.[27] Lastly, to create a disaggregated dataset with a panel structure and fill in the gaps for those years where AmericasBarometer (LAPOP 2008-2014) data was not available I interpolated the missing years with information from the previous survey waves.

4.3 Operationalization of Main Variables

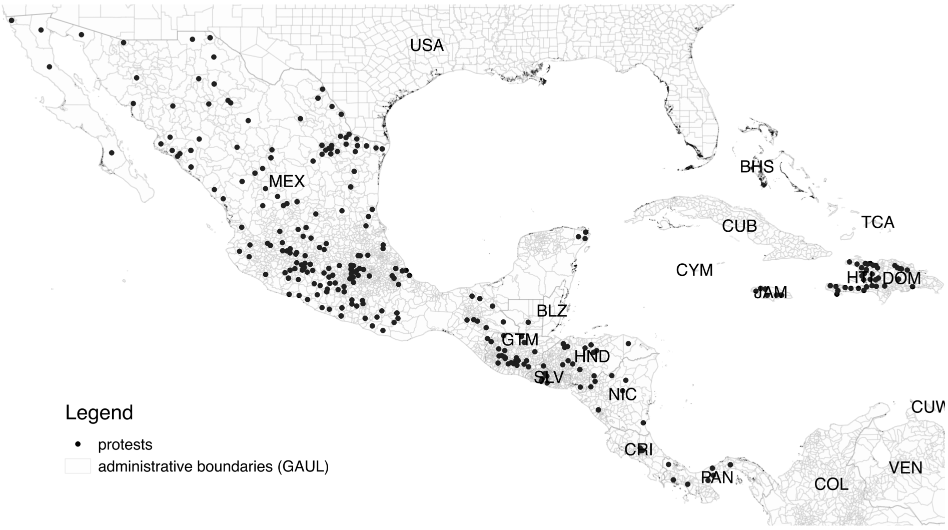
4.3.1 Dependent Variable

The outcome variable *social protest* will enter my model as a binary variable indicating whether a protest event occurred in a municipality in a given year. In total, I extracted eight different types of social unrest from the SCAD (Salehyan et al. 2012), which I regarded as potential consequences of natural disasters and low Quality of Government: 1. organized demonstrations, 2. spontaneous demonstrations, 3. organized riots, 4. spontaneous violent riots, 5. general strikes, 6. limited strikes, 7. anti-government violence, and 8. pro-government violence. If one of the eight conflict categories assumed a value of one in a certain municipality and year, the *social protest* variable was coded as one in that particular municipality and year. In contrast, if none of these eight types of social unrest occurred in a certain municipality and year, the *social protest* variable was coded as zero. Some of my chosen indicators of social protest (anti-government violence and pro-government violence) require a certain level of mobilization and militarization. The reason why I still included them in my analysis is that some countries under study (e.g. Mexico) might already have some semi-permanent militant wing or organizations (Salehyan et al. 2012) in place, which become active in the wake of natural disasters.[28] The geographical distribution of all social protests included in the analysis is visualized in the following map (Map 2), where a dot indicates protest occurrence in a given year and municipality.

[27] The adjustments for four survey waves in 10 different countries included the correction of spelling and punctuation errors, differences in case sensitivity, and the removal of accents and articles. In single cases, I exchanged the entire municipality name used in the AmericasBarometer (LAPOP 2008-2014) by the municipality name used by GAUL (EC-FAO Food Security Programme, 2008) for that particular area. In order to be entirely sure about the location of the assigned municipality, I verified the coordinates by using GoogleMaps.

[28] Two types of social unrest (extra-government violence and intra-government violence) in the SCAD (Salehyan et al. 2012), are not considered in my data set because they do not reflect the discontent of society on the government's performance.

MAP 2: Social Protests in Mexico, Central America and the Caribbean, 2008-2015



4.3.2 Independent Variables

Natural Disasters

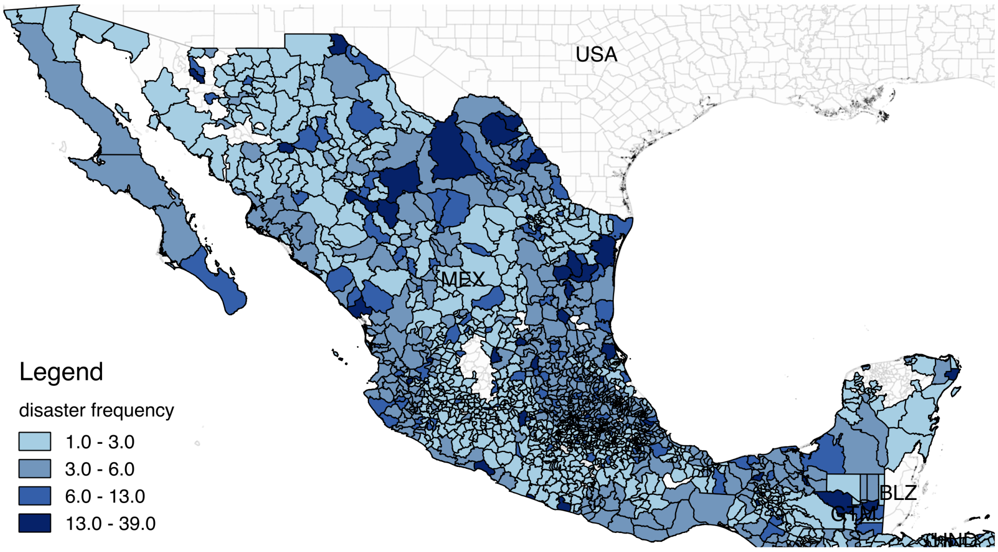
As previously stated, I decided to focus on meteor-hydrological climatic shocks and to exclude geophysical natural hazards (e.g. earthquakes, volcanoes) from my analysis. Droughts, hurricanes and floods are the most common natural hazards in Central America and the Caribbean (Baez et al. 2016) and therefore will be included in the analysis. The three different types of natural disasters (floods, hurricanes and droughts) will enter my model in the form of one single binary disaster exposure variable. This exposure variable will assume a value of one if a municipality has experienced a disaster in the given year, and will take a value of zero if the municipality has not experienced a disaster in a given year.

In order to be considered as a drought in my data set, the drought must meet two conditions. First, it must constitute a severe drought. Following Tollefsen et al. (2012), the drought therefore needs to exceed a SPEI value of -1.5. In addition to that, the drought must last at least three months of consecutive streaks.[29] For hurricanes and floods, I include all natural hazards included in their source data sets because they only include particular severe events. All three natural hazard variables (*drought, hurricane, flood*) will take a value of one if a particular municipality has experienced the specific type of natural hazard in a given year. Tables 2-4 in section 4.4 visualize the number of the natural hazards per type of disaster, municipality and year. In addition, the subsequent Maps (Map 3 and 4) plot the

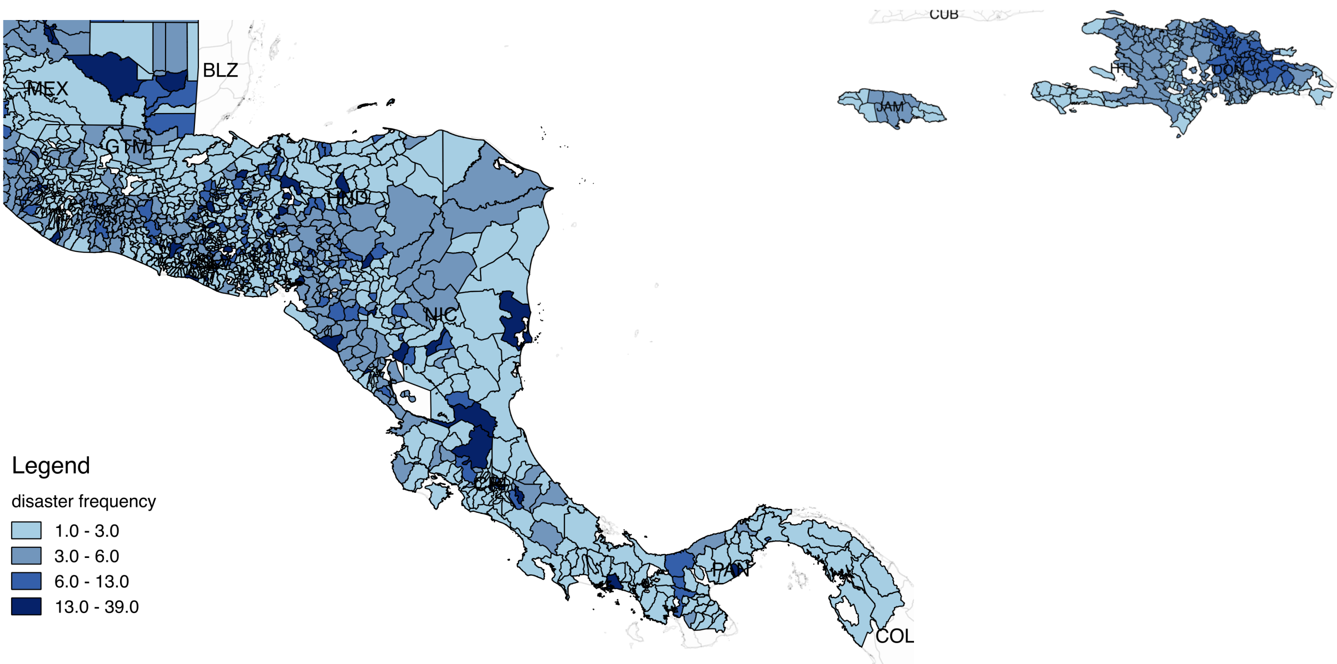
[29] I accessed the SPEI data (Vicente-Serrano et al. 2010) via the *droughtyr_speibase* variable from the PRIO-GRID V. 2.0 data set (Tollefsen et al. 2012), which gives the proportion of consecutive months from 12 months where a certain grid cell has been exposed to a severe drought (value -1.5).

geographical distribution of natural disasters per municipality and frequency, whereby lighter colours indicate less disaster frequency and darker colours stand for high disaster frequency.[30]

MAP 3: Natural Disasters in Mexico, frequency rate for 2008-2015



MAP 4: Natural Disasters in Central America and the Caribbean, frequency rate for 2008-2015



30 For disaster frequency, I first counted all disasters per municipality and year and then calculated the mean frequency rate for each municipality in the period 2008 and 2015.

Moderator Variable: Quality of Government (QoG)

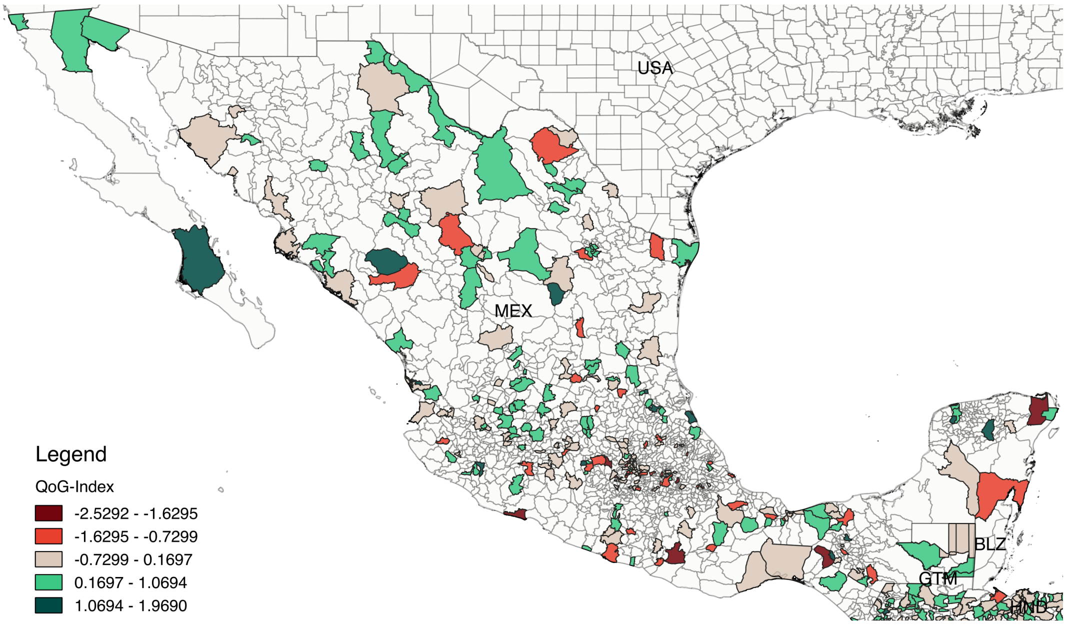
In order to assess the influence of the *QoG* on the core effect between *natural disasters* and *social protest,* I created a QoG-Index. The index is based on three different QoG indicators: 1. Bureaucratic Quality, 2. Rule of Law and 3. Level of Corruption. I chose these three indicators because they are often considered as the core features of QoG (PRS Group 2010, see also: Rothstein & Teorell 2008, Teorell et al. 2017). The information used for the indicators stems from various survey items of the AmericasBarometer (LAPOP 2008-2014). The first indicator (Bureaucratic Quality) is measured by the quality of the municipality service, which is coded as a continuous variable. Based on a Likert scale (Likert 1932) that ranges from zero to seven, respondents were asked to rate on the quality of the municipality service. [31] Furthermore, *Rule of Law* will be measured by citizens' level of trust in the judiciary system. [32] Respondents therefore were also asked to give their opinion on a Likert scale (Likert 1932) ranging from zero to seven. Lastly, the *Level of Corruption* will be captured by the respondents' previous experience with being asked to pay bribes to 1. government officials, 2. municipality officers and 3. the public health service [33]. Respondents could only confirm or deny these questions, which results in three binary variables. My indicator on the level of corruption will also be coded as a binary variable with zero being a proxy for high levels of corruption and one being a measure for low level of corruption. The corruption indicator assumes a value of one if the respondent denied all three questions concerning his previous experience with paying bribes. In contrast, if the respondent confirms one of the three questions, the corruption variable will take a value of zero. For all three indicators —Bureaucratic Quality, Rule of Law and Level of Corruption — the response categories "No Response", "Don't know", "Not asked in this country or year ", and "Not Applicable" were coded as missing observations. The QoG-Index is finally created by summing up the three different QoG indicators. In order to obtain the same mean and standard deviation, all three indicator variables were standardized in advance. The subsequent maps (Map 5 and 6) visualize the level of QoG per municipality. Therefore, I calculated for each municipality in my sample the average QoG rate for the period 2008-2015.

[31] The first QoG indicator is based on the question: "Would you say that the services the municipality is providing to the people are…?", (item sgl1, LAPOP 2008-2014).

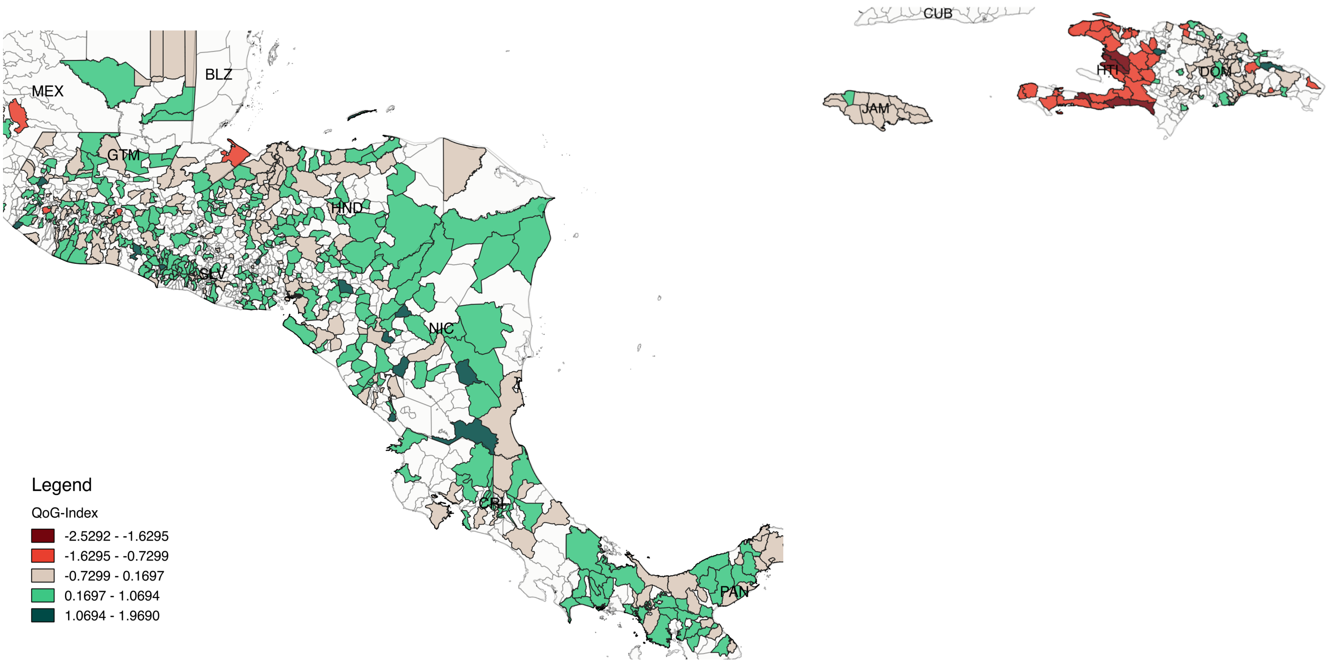
[32] The second QoG indicator is based on the question: "To what extent do you trust the justice system?", (item b10a, LAPOP 2008-2014).

[33] The third QoG indicator is based on the questions: 1. "In the last twelve months, did any government employee asked you to pay a bribe" (item exc6); 2. "In the last twelve months, to process any kind of document in your municipal government, like a permit for example, did you have to pay any money above that required by law? " (item exc11); 3." In order to be seen in a hospital or a clinic in the last twelve months, did you have to pay a bribe? (item exc15, LAPOP 2008-2014).

MAP 5: QoG-Index for Mexico, average rate for 2008-2015



MAP 6: QoG-Index for Central America and the Caribbean, average rate for 2008-2015



4.3.3 Control Variables

In order to eliminate possible sources of endogeneity, I control for several variables that may affect the core effect between natural disasters and social unrest. The selection criterion for these variables are based on reasoning advanced by Ray (2003) or Achen (2005). Thereby, I only consider controls that are likely to influence the relationship between the key explanatory variables and my dependent variable. Most of the control variables stem from the PRIO-GRID data set (Tollefsen et al. 2012) and therefore are at grid cell level. In order to obtain information at the municipality level, I aggregated them on municipality level by taking the mean value for all grid cells that intersects with the same year and municipality.

Population Density

For several reasons, I included population density in my model. First, I need to account for the fact that natural hazards only can turn to natural disasters if the population is affected. Second, the existing literature (Barrios et al. 2006, Brancati 2007, Ahlbom & Povitkina 2016, Ademola et al. 2016) suggests that more densely populated areas are more likely to experience natural disasters. Third, by controlling for population density, I take into consideration that in more densely populated areas, there are more people that can be mobilized for contentious actions (Fearon & Latin 2003, Hendrix & Salehyan 2012). Population density will be measured by the quotient between the sum of the population, provided by the Center for International Earth Science Information Network & Centro Internacional de Agricultura Tropical (CIESIN & CIAT 2005), and the total area covered by land (Weidmann et al. 2010).[34] Population density will enter my model as a static variable because information is not available for the entire study period. Moreover, it will be log-transformed to account for extreme values.

Economic Development

As discussed previously, several authors (Homer-Dixon 1999, Raleigh & Urdal 2007, Brancati 2007) regard the economic development of a country as crucial for both disaster and conflict prevention. Therefore, I include a proxy for the economic development in my model. The nightlight data by the Defense Meteorological Satellite Program's Operational Linescan System (Elvidge et al. 2014) represents the most precise and comprehensive economic development indicator at the subnational level. It provides high-resolution satellite images of the earth during night time. Those areas with a permanent lighting, can be interpreted as better developed, whereas areas without permanent lighting are considered less developed. The data can easily be accessed in calibrated form via the PRIO-GRID data set (Tollefsen et al. 2012). Since data is only available until 2012, I interpolated missing observations with information from the previous years.

[34] Both variables are accessible via the PRIO-Grid 2.0. dataset (Tollefesen et al. 2012).

Ethnic Groups

In view of the various theories on the role of ethnicity in the natural disaster-conflict nexus, I include an indicator of ethnic fractionalization in my model. At the current stage, the Ethnic Power Relations Dataset (GeoEPR Vogt et al. 2015) is the best available data source on the number of marginalized groups per grid cells. Therefore, the GeoEPR (Vogt et al. 2015) has been widely used to model the ethnic power-relations in disaggregated studies. Still, the validity of the data, and the coding procedures in particular, are a debated issue.[35] Since data is only available until 2013, I interpolated observations with information from the previous years.

State Reach

Previous literature has provided good reasons to believe that the level of state reach can determine the occurrence of social protest in the aftermath of natural disasters (Homer-Dixon 2001, Kahl 2006, Raleigh & Urdal 2007, Detges 2016, Eastin 2016, Wood & Wright 2016). Similar to these authors, I assume that a low level of state reach is associated with a higher level of both natural disasters and social protest. Hence, if state reach is low, disaster relief aid cannot be sufficiently provided to the affected areas (Eastin 2016). Furthermore, several scholars (e.g. Weidman et al. 2010) claim that social unrest is more likely to occur where state reach is low. In my model, state reach will be measured by the average distance to capital (in km) in the municipality. The data therefore stem from the cshape dataset (Weidmann et al. 2010).

Urban Share

I add an urban share because it is argued that social protest is more likely to evolve in urban areas (Seter 2016). Accordingly, social protests can easily reach a broad audience in urban areas, which can lead to large scale demonstrations. The urban control variable also accounts for the tendency that governments are more responsive to the concerns and preferences in urban areas (Bezemer & Headey 2008, Wodon & Zaman 2009). Lastly, it addresses possible reporting biases in some of my data sets (flood and social protest data). The information used to construct the urban variable is taken from Globcover (Bontemps et al. 2010), which tracks global land and urban coverage.[36]

Time Trends

Furthermore, by including year-dummies, I control for certain time trends in the data. Hence, it might be the case that due to global warming the total number of natural hazards increases over time. By controlling for time specific effects, I also rule out the possibility that the effect is due to an increasing

[35] The main issue with the GeoEPR (Vogt et al. 2015) is that it does not entail ethnic marginalized groups, that are not active in politics.

[36] The data from GlobCover (Bontemps et al. 2011) can be accessed via PRIO-GRID 2.0. (Tollefsen et al. 2012), which supplies information on the share of urban area per grid cell.

or decreasing trend of social protest occurrence. Most of the countries are still in transition period from autocratic rule to democracy (IMF 2016). Pursuant to the conflict literature (Hegre et al. 2001), transition countries are particular prone to contentious actions, whereas autocracies and full-fledged democracies are less prone to conflict. I therefore expect an increase in the number of social protests during the transition period.

Country-Specific Effects

Lastly, in some of my models I control for country-specific effects that are unobservable or difficult to measure at the subnational level. The different countries in my sample for instance vary in terms of regime type. In line with existing theory (Omelicheva 2011, Quiroz Flores & Smith 2013), I expect that democracies (e.g. Costa Rica) are less likely to experience natural disasters than autocracies (e.g. Haiti). In addition to that, discrimination based grievances should be less visible in democratic regimes (Fearon & Laitin 2003).

4.4 Descriptive Statistics

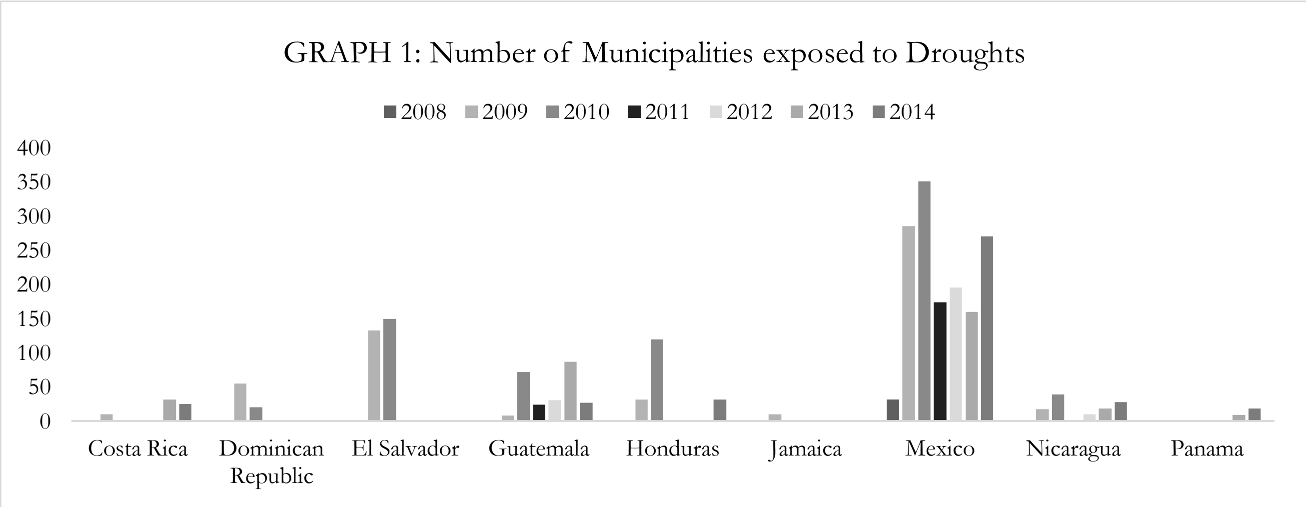
TABLE 1: Summary Statistics of Dependent and Independent Variables

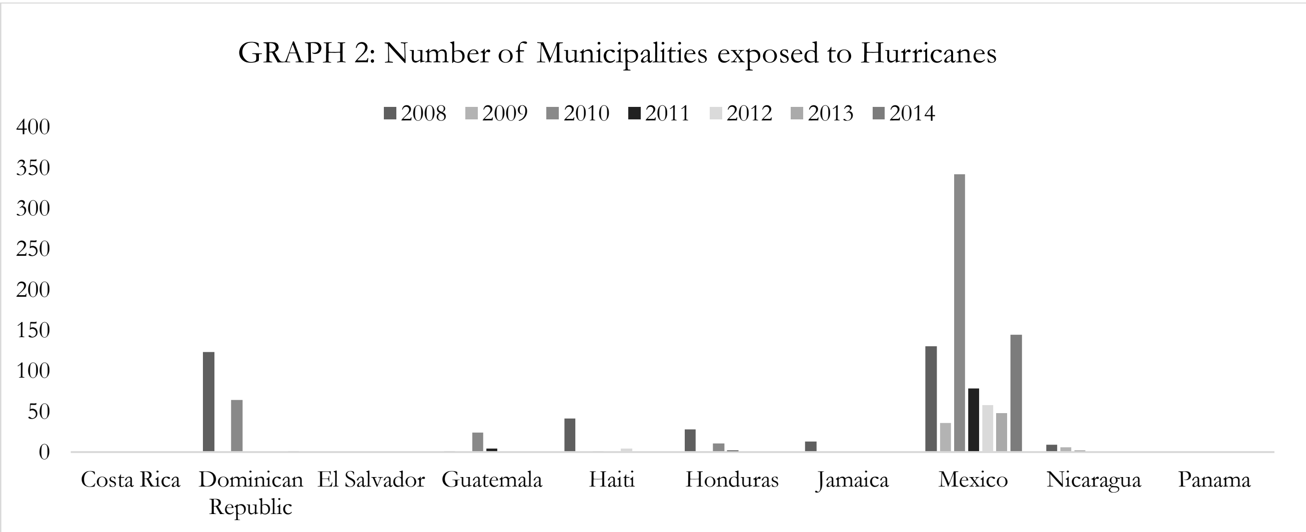
Variable Name	N	Sum	Mean	Min	Max	Median	SD
Social Protest	26440	502	.019	0	1	0	.136
Natural Disaster	26440	9675	.366	0	1	0	.481
Hurricane	23135	1196	.052	0	1	0	.221
Flood	26440	7826	.296	0	1	0	.456
Drought	23135	2485	.107	0	1	0	.309
Economic Development	26440	3469.434	.131	.041	.595	.101	.091
Population Density	26440	6107805	231.006	0	3670.405	116.464	401.14
Ethnic Groups	26440	11346	.429	0	2	0	.506
Distance to Capital	26440	9039542	341.889	6.837	3623.609	171.214	397.174
Urban Share	26440	9472.050	.358	0	14.441	.0062	1.343
QoG-Index	4214	365.772	0.09	-3.46	3.03	.1632	0.89
Bureaucratic Quality	4214	9.661	0.00	-1.92	1.85	-.0086	0.46
Rule of Law	4214	215.345	0.05	-1.56	1.63	.0366	0.44
Corruption Level	4214	151.089	0.04	-2.33	0.85	.1706	0.43
Infrastructure	4214	4044.441	0.96	0.15	1.00	1	0.09

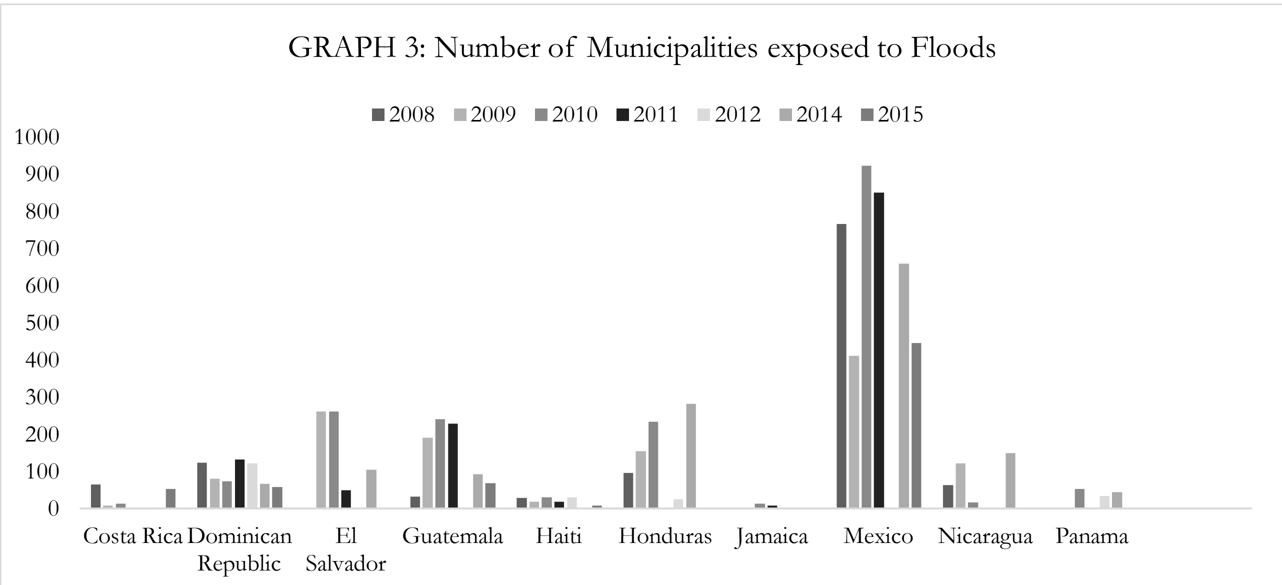
Table 1 provides information on the distribution of the data underlying the t- tests. The number of observations for droughts and hurricanes is reduced because data is not available for 2015. Moreover, it becomes obvious that a relatively low number of cases with social protests (502) will be compared to a high number of cases without social protests (25.938). The total number of natural hazards per municipality varies with respect to country and disaster type, which will be visualized in Graphs 1-3. In all the graphs, Mexico stands out because of its large size and its high number of municipalities (1. 879).[37] Yet, it is important to note that this does not imply that the vulnerability of Mexican municipalities to natural hazards is higher compared to other municipalities in the Central American and Caribbean region. In contrast, it simply reveals that larger countries have a higher probability of experiencing natural hazards because of their territorial size. Another peculiarity that can be derived from the distribution of disasters per municipalities (Graphs 1-3) is that some countries did not experience a certain type of natural disasters during the period under study. The two neighbouring countries Panama and Costa Rica, and also El Salvador were not exposed to any large-scale hurricane between 2008 and 2014.[38]

[37] In general, the number of municipalities per country does not always increase with the size of the country. Nicaragua, for instance, has a larger territorial size compared to the Dominican Republic (see: Map 1 above). Yet, the total number of municipalities in the Dominican Republic (160) exceeds the number of municipalities in Nicaragua (151).

[38] In view of the spatial proximity of the countries this could be explained by geographical factors.


GRAPH 1: Number of Municipalities exposed to Droughts
2008
2009
2010
2011
2012
2013
2014
400
350
300
250
200
150
100
50
0
Costa Rica
Dominican Republic
El Salvador
Guatemala
Honduras
Jamaica
Mexico
Nicaragua
Panama


GRAPH 2: Number of Municipalities exposed to Hurricanes
2008
2009
2010
2011
2012
2013
2014
400
350
300
250
200
150
100
50
0
Costa Rica
Dominican Republic
El Salvador
Guatemala
Haiti
Honduras
Jamaica
Mexico
Nicaragua
Panama


GRAPH 3: Number of Municipalities exposed to Floods
2008
2009
2010
2011
2012
2014
2015
1000
900
800
700
600
500
400
300
200
100
0
Costa Rica
Dominican Republic
El Salvador
Guatemala
Haiti
Honduras
Jamaica
Mexico
Nicaragua
Panama

4.5 Method

To examine the link between *natural disasters, QOG and social protest* a quantitative approach will be used. In view of the dichotomous character of the dependent variable *social protest*, I will employ a logistic regression model for my panel data analysis:

$$ln \frac{P(x_{it})}{1 - P(x_{it})} = \beta_0 + \beta_1 x_{it}$$

The logistic regression model uses maximum likelihood estimation (MLE) to compute the coefficients of my explanatory variables. For both model specifications, the minimum sample size for logit regression is surpassed, which will ensure reliable estimates.[39] Furthermore, multicollinearity of the independent variables should be low in logit regression models (Long 1997). This will be checked through subsequent robustness tests. Moreover, to account for heteroscedasticity between the observations, robust standard errors are recommended in time series analyses.

My main model specifications for the core effect without and with control variables read:

(1) $P(P_{it} = 1) = \beta_0 + \beta_1 \, ND_{it} + \varepsilon_{it}$

(2) $P(P_{it} = 1) = \beta_0 + \beta_1 \, ND_{it} + \beta_2 PopD_{it} + \beta_3 Econ_{it} + \beta_4 Ethnic_{it} + \beta_5 CapD_{it} + \beta_6 Urban_{it} + \beta_7 Country_{it} + \beta_8 \, Year_{it} + \varepsilon_{it}$

In order to assess whether *QoG* moderates the core effect between *natural disasters* (*ND*) and *social protests* (*P*), I will include an interaction term between *ND* and *QoG* (*ND *QoG*). The model specifications for the moderator effect without and with control variables read:

(3) $P(P_{it} = 1) = \beta_0 + \beta_1 \, ND_{it} + \beta_2 QoG_{it} + \beta_3 ND_{it} * QoG_{it} + \varepsilon_{it}$

(4) $P(P_{it} = 1) = \beta_0 + \beta_1 \, ND_{it} + \beta_2 QoG_{it} + \beta_3 ND_{it} * QoG_{it} + \beta_4 PopD_{it} + \beta_5 Econ_{it} + \beta_6 Ethnic_{it} + \beta_7 CapD_{it} + \beta_8 Urban_{it} + \beta_9 Country_{it} + \beta_{10} \, Year_{it} + \varepsilon_{it}$

[39]Following guidelines from Peduzzi et al. (1996), the minimum sample size for logit regression should be calculated by: $N = 10 \, k \, / \, p$, where N corresponds to the sample size, k to the number of covariates and p to the proportion of positive cases in the sample. The application of the formula (N= 10*8/0.02) results in a threshold of 4000 observations for my first model specification and 1600 observations for my second model.

V. Results

The logit regression outputs for the core effect and the moderator effect are presented below in Table 2 and Table 4. The logistic coefficients reveal whether the variables in question are significant and whether they positively or negatively affect the outcome, in my case the occurrence of social protest. Accordingly, positive values suggest that popular protest becomes more likely, while negative ones point towards the opposite direction.

5.1 Logit Regression Output for Main Effect

TABLE 2: Logit Regression Output for Main Effect

DV: Social Protest	**M 1**	**M 2**	**M 3**	**M 4**	**M 5**	**M 6**	**M 7**	**M 8**	**M 9**	**M 10**
Natural Disaster	0.279** (0.087)	0.248** (0.087)	0.269** (0.088)	0.271** (0.087)	0.324** (0.088)	0.273** (0.087)	0.300** (0.089)	0.191** (0.096)	0.157 (0.098)	0.240** (0.115)
Population Density (log)		0.162** (0.064)					0.458** (0.095)	0.466** (0.097)	0.364** (0.092)	0 (.)
Economic Development			0.989 (0.847)				-3.919** (1.281)	-4.094** (1.327)	-2.576* (1.414)	2.678 (2.04)
Ethnic Groups				-0.607** (0.171)			-0.655** (0.171)	-0.671** (0.172)	-0.386** (0.178)	-0.613 (0.454)
Distance to Capital					0.000** (0.000)		0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.000 (0.001)
Urban Share						0.113** (0.042)	0.100* (0.057)	0.102* (0.057)	0.104** (0.053)	0 (.)
country 0/1	No	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	Yes
N	26312	26312	26312	26312	26312	26312	26312	26312	26312	2240

Note: Robust standard errors in parentheses, clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$.

The models presented in Table 2, yield first support for the expectation of my first hypothesis claiming that *natural disasters* increase the likelihood of *social protest*. Almost all models display a positive and significant effect of *natural disasters* on the likelihood of *social protest*. Even when controlling for other potential explanatory variables (M1-M7) and when accounting for time (M8) and municipality specific effects (M10) the statistical relationship remains significant.

The results of the control variables are largely in line with my theoretical expectations. The positive and significant coefficient of *population density* reveals support for the theoretical argument that population density increases the likelihood of social protests after natural disasters. This can either imply that natural disasters have a larger impact on more densely populated areas. Yet, this can also be an indicator for the fact that more densely populated areas are more likely to protest because mobilization of people is facilitated. In M 3, I test whether the *economic development*, as measured by the average night-time light emission, affects the likelihood of social protests after natural disasters. The economic indicator is insignificant in that particular model, which could be due to a selection bias in the data.[40] When adding time, country and municipality specific effects in the subsequent models (M 8- M 10), the economic variable turns significant. Here, the sign of the economic variable is negative, which corroborates the thesis that regions with a high economic development are less affected by natural disasters and thus protest likelihood is reduced. In view of the large standard errors of my economic variable, this interpretation needs to be taken with caution.

Moreover, the results in Model 5-8 display a positive link between high *distance to capital* and the likelihood of protest occurrence. This implies that low state capacity, measured by high *distance to capital* can trigger social protests in the aftermath of natural disasters. The results of the urban variables are also in line with existing theories suggesting a positive association between the *share of urban areas* and my outcome variable. It provides support for the theory that urban areas are more protest experienced than rural areas and therefore are more likely to protest after natural disasters (Seter 2016). Lastly, the ethnicity variable behaves in more surprising manners. Accordingly, *ethnic fractionalization* is associated with a lower risk of social protest. The reasoning for that findings will be discussed in the final section.

Seeing that the coefficients in the logit regression output do not give evidence about the size of the effect, I calculated the marginal effects for Models 6-8. Marginal effects are a modification of the method of first differences, which can easily be computed and give an impression on the size of effects (King 1998). [41] The marginal effects are calculated for a discrete change of the disaster variable from 0 to 1 by holding all other variables at their means. Table 3 depicts the marginal effects for the logit regression results. Accordingly, when including all control variables in M6*, the probability of social protests increases by 0.6 %. The size of effect is further reduced when including time and country dummies in M7* and M8*.

[40] Since there is evidence that regions with less economic power are also more vulnerable to natural disasters, the occurrence of disasters could at least in part reflect the economic development of the state (Eastin 2016). Statistical models that capture both natural disasters and economic development therefore can cause spurious correlations (ibid.). This type II error is often indicated by an increased size of the standard errors (ibid.), which is the case in M 3. In my case, the selection bias could stem from the flood data because it does not measure pure natural hazards but considers factors such as the actual damage of the hazard.

[41] For the marginal effect in M7-M9 I used the margins command in Stata. Marginal effects cannot be computed for the FE model (M 10) because marginal effects depend on the individual (municipality) effects that I hold constant in the FE model.

TABLE 3: Marginal Effects for Core Model Specifications

DV: Social Protest	M 6*	M 7*	M 8*
disaster (d)	0.006**	0.004**	0.003*
	(0.002)	(0.002)	(0.002)
year 0/1	No	Yes	Yes
country 0/1	No	No	Yes
N	26312	26312	26312

Marginal effects; standard errors in parentheses, clustered on municipalities; (d) for discrete change of disaster variable from 0 to 1. * $p < 0.10$, ** $p < 0.05$.

5.2 Robustness Checks for Main Effect

As announced above, I conducted several robustness checks to determine the relationship between natural disasters and social protest. First, the panel character of my data allows the estimation of fixed effect models. This type of model controls for all time-invariant variation between the municipalities that is not captured by the control variables (Allison 2009).[42] By using a fixed effect model, every municipality receives multiple treatments, which eliminates a large part of the error variance and makes the results more robust (ibid.). The downside of the fixed effect model is that it cannot estimate the coefficients for variables that do not vary within municipalities. Consequently, all static control variables (e.g. population density, urban share) drop out. The results of the municipality fixed effect model are reported in Table 2, M 10. Interestingly, when including the municipality fixed effects, all control variables turn insignificant, whereas the disaster variable remains significant. This provides further support for my first hypothesis that natural disasters increase the likelihood of social protests.

Second, I estimated a complementary log-log regression model because of the low frequency of social protest occurrence (Fox 2015). The complementary log-log function approaches the asymptotes of zero and one asymmetrically (ibid.).[43] Yet, in most of the cases the results do not substantially differ from a classic logit model (ibid.), as also in my case. Therefore, I stick to the classic logit model.

Third, I recalculated all models with different lag structures of the disaster variable in Table A3.[44] For that purpose, I re-estimated all models lagging my main independent variable by one and two years.

[42] I chose the fixed effect (FE) model over the random effect (RE) model based on Hausman test (Durbin 1954, Wu 1973). The Hausman test revealed that individual effects of the municipalities are correlated with the other regressors in the model. This turns the FE model consistent and the RE model inconsistent.

[43] The complementary log-log function approaches values of zero slowly and values of zero rapidly (Fox 2015). Results can be found in Table A2 in the Appendix.

[44] Results are displayed in Table A3 in the Appendix.

Hence, it might be the case that the social response to natural disasters does not occur as immediately as suggested by my theory. Pursuant to the literature (Burke et al. 2009, Burke et al. 2015), there is reason to believe that the social response to natural disasters occurs delayed when people first need to cope with the immediate consequences of the disaster. The lagging of the disaster variable does not improve my results substantially. When calculating municipality fixed effects in Model 8 and Model 9, the lagged disaster variable even loses its significance.

Fourth, I specified my models based on different disaster types because several authors (Omelicheva 2011, Bergholt & Lujala 2012, Noy 2016, Wood & Wright 2016) note that the impact of different types of natural varies. It is argued that slow-onset disasters such as droughts less often lead to spontaneous events in the form of social protests than rapid onset-disasters (Wood & Wright 2016). Accordingly, slow-onset disasters emerge over time and therefore provide better opportunities for the government and the population to react and adapt (ibid.). Therefore and because of other potential differences between natural disasters (e.g. predictability, frequency, extent of damage), I tested for every type of disaster separately. The results display positive signs for all different types of natural disasters. Yet, the level of significance as well as the size of the effects vary slightly between the different types of natural disasters.[45] Rapid-onset disasters, such as hurricanes and floods, appear to have a more determining effect than slow-onset disasters in the form of droughts, which is in line with existing theory.

Fifth, I restricted my analysis to Mexico because it accounts for about half (1.879) of the municipalities (3.289) in the first part of the analysis. Across all models, the disaster variable reveals a positive and significant association with my outcome variable. In addition, all control variables are in line with previous models.[46] On the one hand, this finding corroborates my hypothesis, on the other hand, it also could imply that the findings could be driven by the Mexican case. The latter option is ruled out by excluding Mexico from the analysis and by still obtaining the same results.

Lastly, to account for potential post-treatment biases, I also decided to re-run my models by using the lagged form of my economic variable. In addition, to the detriment of exogeneity, I checked whether my core effects in M7-M10 are also robust when excluding the economic variable. The regression outputs for these additional model specifications do not substantially change my findings.[47] According to Acharya et al. (2016), intermediate variables biases occur when the post-treatment variable is non-causally linked to the outcome variable. In my case, there are good reasons to assume that my economic variable is non-causally linked to the core independent variable. Therefore, the economic

[45] Results are displayed in Table A4 in the Appendix. The drought variable is lagged because it can be assumed that citizen's response to droughts occurs delayed (see also: Wood & Wright 2016).
[46] Results are displayed in Table A5 in the Appendix.
[47] Results for the model specification with the lagged economic variable are displayed in Table A6 in the Appendix.

variables could absorb some of the explanatory power of my treatment variable, which would result in inconsistent estimates (Acharya et al. 2016). The same bias could apply for the population variable. Since migration often follows natural disasters, the size of population could be reduced in the aftermath of the disaster. Yet, in view of its static character, it does not make sense to transform the population variable. Acharya et al. (2016) discuss several estimation strategies that can be helpful to detect competing explanations. They will be further discussed in the final section.

5.3 Logistic Regression Output for Moderator Effect

TABLE 4: Logistic Regression Output for Moderator Effect

DV: Social Protest	**M 1**	**M 2**	**M 3**	**M 4**	**M 5**	**M 6**	**M 7**	**M 8**	**M 9**	**M 10**	**M 11**	**M 12**
Natural Disaster	0.425** (0.135)	0.381** (0.134)	0.292** (0.141)	0.255* (0.141)	0.286** (0.140)	0.302** (0.142)	0.335** (0.140)	0.286** (0.140)	0.331** (0.145)	0.205 (0.157)	0.220 (0.163)	0.229 (0.215)
QoG-Index		-0.505** (0.090)	-0.349** (0.100)	-0.306** (0.101)	-0.345** (0.101)	-0.343** (0.102)	-0.367** (0.097)	-0.344** (0.101)	-0.289** (0.104)	-0.292** (0.106)	-0.0406 (0.102)	0.0481 (0.163)
Natural Disaster # QoG-Index			-0.306** (0.119)	-0.302** (0.122)	-0.304** (0.121)	-0.305** (0.119)	-0.293** (0.117)	-0.307** (0.119)	-0.269** (0.117)	-0.275** (0.122)	-0.257** (0.119)	-0.408** (0.202)
Population Density (log)				0.250** (0.092)					0.685** (0.177)	0.703** (0.181)	0.803** (0.221)	0 (.)
Economic Development					0.723 (1.128)				-3.247* (1.777)	-3.422* (1.842)	-3.669* (2.196)	-5.965 (5.078)
Ethnic Groups						-0.394 (0.277)			-0.419 (0.282)	-0.456 (0.288)	0.028 (0.277)	-0.549 (0.802)
Distance to Capital							0.001** (0.000)		0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.000 (0.001)
Urban Share								0.036 (0.049)	-0.066 (0.084)	-0.068 (0.085)	-0.083 (0.076)	0 (.)
country 0/1	No	No	No	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	No	No	Yes
N	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	622

Note: Robust standard errors in parentheses, clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$.

Table 4 displays the results for my second model specification. When restricting the sample to those municipalities where AmericasBarometer (LAPOP 2008-2014) is available, the number of observations drops from 26.312 to 4.214. Despite of the reduced sample size, the core effect remains significant in M1 and M2 when including control variables. Adding the QoG variable in M3, it reveals a negative and significant relationship between natural disasters and protest occurrence. This implies that the likelihood of social protest decreases in municipalities with a higher level of QoG, which is in line with my second hypothesis. After including the interaction term in M4, both the disaster variable and the QoG lose significance but still display the correct direction of effects. Among all models (M4-M12) the interaction term reveals a negative and significant effect on the core effect between natural disasters and social protest. Even when including other explanatory variables in M5-M9 and when controlling for time, country and municipality specific effects in M10-M12, the moderator effect remains significant. The signs of the control variables correspond at large to the signs in my first model specification. Only the coefficient of the economic variable in M 5 points in the opposite direction.[48] Yet, when accounting for year and country specific effects in M11 and M12, the economic variable displays the expected negative sign. Therefore, it can be concluded that also in my second model specification the economic development of a country is crucial for the prevention of social protest. Besides the economic variable, other control variables that previously have been significant turn insignificant when including the interaction term. Both the number of *ethnic groups* and the *share of urban area* are insignificant across all models. Interestingly, the ethnicity variable changes the sign of the coefficient from negative to positive when accounting for country specific effects in M11. The positive sign of the ethnic variable could have provided support for existing theories by revealing that ethnicity increases the likelihood of conflicts after natural disasters in some countries. However, since the coefficient is not significant it does not allow for any deeper interpretations.

Scientists (Ai & Norton 2003, Norton et al. 2004, Cornelißen & Sonderhof 2009) caution against interpreting coefficient signs and significance level of the interaction term in the logit regression output. For the final interpretation of the interaction effect, I therefore first calculated the marginal effects for a change from QoG = -3.5 to QoG= 3.0 by holding the disaster variable at one and all control variables at their mean. The predictive margins are reported in Table 5.[49] The rows in bold are particularly interesting for the interpretation of the interaction effect since they provide evidence on the difference between low and high levels of QoG on condition that disaster equals one. Accordingly, in M9* the likelihood of social protest is decreased by 0.261 (26.1 %) if QoG changes from zero to one, holding the disaster variable at one and all control variables at their means.[50] After including year-dummies in M10*, the effect of disasters on social protest decreases by 0.249 (24.9%) if QoG changes from zero to one, holding the disaster variable at one and all control variables at their means. Lastly, when including the country-dummy in M11*, the effect of QoG on the core effect between natural disasters and social protests drops notably. In this last model, QoG only reduces the likelihood of social protest after natural disasters by 0.0737 (7.37%). Second, to verify the existence of the interaction term, creating a graph is recommended (Norton et al. 2004). Graphs 4-5 visualize the interaction terms in M9*-M11*.

[48] I checked for multicollinearity in my model by using the variance inflation factor (VIF) STATA command. The mean VIF for my independent variables is 1.61, which indicates that multicollinearity is not a serious problem in my model.

[49] I did not collapse the QoG-Index but calculated the marginal effects for its maximum and minimum value. I restrict my calculations to M9*-M11* because marginal effects cannot be calculated for the fixed effect model (M12).

[50] The marginal effects are calculated by employing the difference in difference (DID) strategy. The DID computes "the difference of the mean outcomes of treated and control groups" (Lechner 2010, p.176), which in my case corresponds to Disaster=1 & QoG 3.5 minus Disaster= 1 &QoG= 3.0.

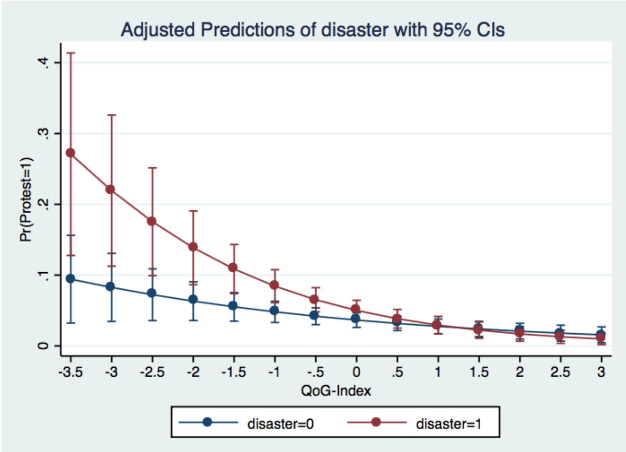
The red curve depicts the marginal effects conditional on natural disasters equals one, whereas the blue stands for the marginal effects conditional on natural disaster equals zero. All three graphs show that low levels of QoG notably increase the likelihood of social protests if the municipality experienced a natural disaster.

TABLE 5:
Adjusted Predictions of Natural Disasters (D)

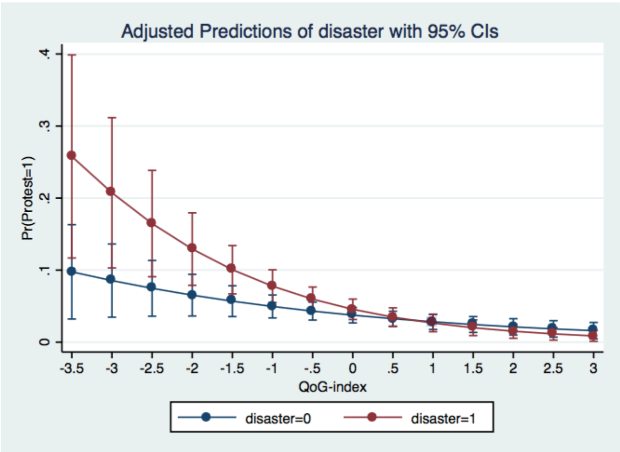
D	QoG	M9*	M10*	M11*
0	-3.5	0.0942	0.0976	0.0306
		(0.0316)	0.0334	(0.0124)
1	**-3.5**	**0.2708**	**0.2577**	**0.0873**
		(0.073)	(0.072)	(0.0312)
0	3.0	0.0156	0.0159	0.0237
		(0.0057)	0.0058	(.0083)
1	**3.0**	**0.0098**	**0.0086**	**0.0136**
		(0.0040)	(0.0037)	(0.0053)
	country 0/1	No	No	Yes
	year 0/1	No	Yes	Yes
	N	4.214	4.214	4.214

Note: Robust Standard Errors in parentheses clustered on municipality.

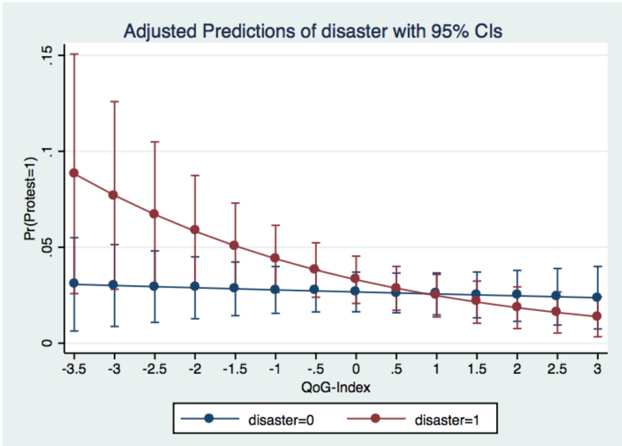
GRAPH 4:
Adjusted Predictions of Disasters for M9*



GRAPH5:
Adjusted Predictions of Disasters for M10*



GRAPH 6:
Adjusted Predictions of Disasters for M11*



5.4 Robustness Checks for Moderator Effect

To ensure the robustness of my results, I recalculated all models with a two-year lag of the *QoG* variable and a one-year lag of the disaster variable. [51] Thereby, I account for the possibility that the level of *QoG* measured by the survey data is affected by the disaster itself. This does not rule out the possibility that previous disasters have had an effect on the level of *QoG* in the municipality. The inclusion of these lagged explanatory variables turns the two core variables *QoG* and *Natural Disaster* significant and my interaction term insignificant, which does not provide support for my second hypothesis. Yet, all coefficients still point in the expected direction and my first hypothesis is further sustained.

In addition to that, I re-estimated the regression models by taking only the representative survey waves of the AmericasBarometer (LAPOP 2008-2014) into account. Survey waves 2012 and 2014 are both included because they are representative at the municipality level. Due to linear interpolation between the survey waves, the calculations are based on a sample that covers the period between 2012 and 2015. When restricting the sample to about half of the observations, the coefficient of the disaster variable in Table A9, M1 suddenly reverses and becomes insignificant. The insignificance, this does not contradict my theory. One possible explanation for the reversal from positive to negative could be that there are fewer natural disasters in the second period of analysis (2012-2015) than compared to the first period (2008-2011).[52] Despite of the decline in the natural disaster data, the interaction term displays a negative and significant coefficient in all of the models (Table A9, M3-M11), which further strengthens my second hypothesis.

Subsequently, I restricted my analysis to Mexico, because it accounts for about one fourth (1.012) of the municipality-year observations with *QoG* information (4.212).[53] For Mexico, I did not find a significant interaction term suggesting that my core findings are not mainly driven by Mexico. Moreover, I verified my results by including a different infrastructure measure. Using AmericasBarometerdata (LAOPOP 2008-2014) I constructed an infrastructure indicator that takes the value of zero if the respondent considered either “roads”, or “water”, or “housing”, or “transportation” as the major problem in the country. In contrast, if neither of the four options were mentioned by the respondent, the infrastructure variable assumes a value of one.[54] The sign of the infrastructure variable

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[51] Results are displayed in Table A7 and Table A8 in the Appendix.
[52] The decline in natural disasters in the second period of analysis (2012-2015) is not only driven by the fact that there is no hurricane and drought data available for the year 2015.
[53] Results can be found in Table A9 in the Appendix.
[54] The information for the infrastructure indicator stems from the a4 variable of the AmericasBarometer (item a4, LAPOP 2008-2014), which is based on the question: “In your opinion, what is the most serious problem faced by the country?”.

pointed in the same direction as the sign of the distance to capital variable used in my model specifications. However, it did not reach the level of significance.[55]

Lastly, I checked whether the effect of different QoG indicators varies. According to Table A11 in the Appendix, both *corruption* and *rule of law* are negatively and significantly correlated with social protests in M3 and M4, whereas the coefficient of *quality of bureaucratic service* is negative but not significant. In contrast, when multiplying the different indicators of *QoG* with the *natural disaster* variable, only the interaction term between *natural disasters* and *quality of bureaucratic service* proved significant, whereas the two other interaction terms prove insignificant. This implies that civil society during normal times is more likely to protest against low levels of corruption and a weak rule of law than against poor quality of municipality service. Yet, during extreme events in the form of natural disasters, civil society is particularly likely to protest against the poor quality of the municipality service. Even though the interaction terms for two of the *QoG* indicators do not prove significant in this model, they still might exert a significant influence in my core model specification. Hence, there are also reasons to believe that social protest occurs after natural disaster when a combination of the three does not fulfil the expectations of civil society.

VI. Discussion

This section discusses how well the research question "Does QoG prevent social protests in the aftermath of natural disasters?" has been addressed. Therefore, I will shortly summarize the main findings and link them to existing theoretical beliefs in the literature. Thereafter, I will point at existing methodological problems and limitations of the thesis and provide implications for further research.

6.1 Interpretation of Findings

The regression outputs for my main effect provides further support for the theory that natural disasters increase the likelihood of social protests. The findings are robust when controlling for other explanatory variables and accounting for time trends, and country and municipality specific effects. Yet, in substantive terms the effect of natural disasters on social protest is rather neglectable. Subsequently, I conclude that my first hypothesis "*Natural Disaster increase the likelihood of Social Protest*" only receives modest support. This result makes a conditional relationship even more likely. By revealing the interaction effect in my second regression output, I then provide particular support for the claim that natural disasters are neither a necessary nor a sufficient condition for conflicts. Without question,

[55] Results are not shown in the Appendix.

several other factors unrelated to natural disasters, can be the source of social protest. More importantly, my second logit regression output reveals that there are good reasons to assume that natural disasters do not per se provoke social protest but are based on conditional factors, such as the level of QoG in the municipality. The results for the interaction effect unfold a substantial difference in the likelihood of social protest between municipalities with lower levels of QoG and municipalities with higher levels of municipalities. Since these differences are substantial, I affirm the second hypothesis "*QoG moderates the effect between natural disasters and social protest*". Furthermore, I find that this effect is particularly pronounced with respect to the bureaucratic quality of the state, whereas rule of law and the level of corruption exhibit a somewhat weaker effect. For bureaucratic quality, I use a survey item that specifically asked about the performance of the municipality. In contrast, the two other QoG indicators were primarily measured based on survey items related to the performance of the national government. One could therefore conclude that the local performance, in particular, matters in the wake of natural disasters.

Existing literature on natural disasters and intrastate conflicts or non-state conflicts often perceive the argument that natural disasters increase cooperation and social cohesion (Bergholt & Lujala 2012, Slettebak 2012) as a competing argument to their own theoretical beliefs. Yet, by focusing on contentious actions that are solely directed against the state, my findings do not assume that conflict between different groups arises. The coefficients of the ethnicity variable in all of my models suggest that the number of ethnic groups negatively affect the core effect between natural disasters and social protest occurrence. If we believe the conflict literature (Montalvo & Reynal Querol 2005, Esteban & Schneider 2008), it is a challenging endeavor to justify the direction of this effect. However, it might be an indicator for the theoretical claim that ethnicity becomes less important in the wake of natural disasters, because cooperation and social cohesion replace mistrust and inter-group competition (Akcinaroglu et al. 2011, Omelicheva 2011, Bergholt & Lujala 2012, Slettebak 2012). Another, reasoning for the divergent findings could be the kind of data I used to capture the role of ethnicity in my statistical model. Similar to the MAR data set (CIDCM 2009), the GeoEPR dataset (Vogt et al. 2015) only includes politically relevant groups. Moreover, scientists (Reynal-Querol 2002, Montalvo & Reynal-Querol 2005) contend that measures of ethnic polarization outperform indicators of ethnic fractionalization. Hence, ethnic polarization does not only consider the total number of ethnic groups but also weights the them according to their relative size (ibid.).

6.2 Limitations

Despite of my robust results, the interpretation of my findings must be treated with caution. First, my findings lose quality because it is not temporally disaggregated. Hence, in order to be able to directly link the protest event to the natural disaster, a finer temporal resolution of the data is needed (Ide 2017). In my case, the temporal over-aggregation is particularly problematic if a municipality experienced social protest in the beginning of a year and a natural disaster in the end of the year. Unless, the municipality did not experience a disaster in the previous year, one can be certain, that for the current year these two events are spuriously correlated in my analysis. In my robustness checks, I sought to address these issues by employing different lag structures of the treatment variables. Still, the possibility persists that social protests unrelated to natural disasters are considered in the analysis. Even though all datasets considered in this thesis have information at the monthly level, I decided against the temporal disaggregation of the data.[56] This is mainly because the aggregation of monthly data at municipality level is a time-consuming process if one wants to preserve the temporal variation using QGis. Last but not least, by not using monthly data, I also circumvent the disadvantage of not being able to detect long-term effects with my data. Despite of the potential overestimation of the core effect, one can at least exclude the possibility of reverse causality because of the exogenous nature of the disaster variable. This is particularly important because reverse causality has the potential to entirely distort causal inference.

Second, my estimates could be biased since I do not account for spatial autocorrelation. Pursuant to Harrari & La Ferrara (2014), this type of error is particularly likely when studying localized conflicts such as social protests, but is less frequently the case when studying civil wars (Harrari & La Ferrara 2014). In my model, spatial autocorrelation can either stem from direct contagion effects of the dependent variable or from spatial correlation of the covariates (see also: Harrari & La Ferrara 2014). If social protests in one municipality, for instance, spill over to the neighbouring municipality, one can speak of direct contagion effects. The correlation of the two protest events in the neighbouring municipalities can lead to an overestimation of my actual sample size and therefore lead to biased estimates. Furthermore, localized features thereby can be easily overstated, which causes an omitted variable bias. Several statistical models can be employed to address spatial autocorrelation. For panel data, spatial autoregressive models only recently have been developed (e.g. LeSage & Pace 2009, Elhorst 2009). One can, for instance estimate a dynamic, spatially autoregressive Durbin model (Elhorst, 2009), which accounts for both spatial and temporal autocorrelation. The computation of this model is intensive and therefore has not been employed in this thesis.

[56] In order to obtain the QoG data at monthly level, one could use the date of interview, given in the AmericasBarometer (2010-2014).

Third, there are good reasons to assume that I have not sufficiently addressed the post-treatment bias. According to Acharya et al. (2016), about two third of the studies in political sciences suffer from a so called intermediate variable bias. This fact does not mitigate the severity of the bias but calls for the urgent need for the development of further methodological approaches that allow scientists to better deal with these issues. In order to identify and deal with competing mechanisms, Acharya et al. (2016) propose the instrumentalization of controlled direct effects. Controlled direct effects can be obtained by holding the treatment and the posttreatment variable- in my case the economic variable- fixed at a certain value (Acharya et al. 2016). Based on sequential g-estimation, the direct effect of the treatment variable on the outcome variable then can be tested without the intermediate variable bias (ibid.). The problem with this approach is that it rests on strong assumptions, which are not met by my statistical models, not least because my regression model violates the linearity-assumption.[57] The average control direct effects can, in principal, also be computed for non-linear models (Acharya et al. 2016). Yet, this requires further computing and modelling (Acharya et al. 2016, see also: Robins 1997), which is beyond the scope of this thesis.

6.3 Future Research

The data availability allows conducting analyses at the survey respondent-level. Based on a sample size exceeding 100.000 observations, future studies could examine the individual motives of protesters more precisely and thereby better link social protest events to natural disasters. On the one hand, this reduces the possibility of studying social protests that are unrelated to natural disasters. Yet, on the other hand, a time-series cross sectional analysis then would not be feasible anymore because survey respondents are not interviewed on a year by year basis. In addition, the core effect between natural disasters and social protests can easily be recalculated at the grid-level, which increases the precision of my estimates. Nevertheless, I decided to stick to the municipality level because it ensures a better comparability between the two core model specifications (main effect and moderator effect).

Future data processing steps could involve the extension of the geo-referenced data period to the 2004 and 2006 survey waves (LAPOP 2004-2014). Survey wave 2006, for instance, provides information on all the countries that have been studied in this thesis. While for some survey respondents, the geographic information is provided, for others the geographic labels are missing. Due to time constraints, I decided against processing the inconsistent municipality variable for survey wave 2006. All survey waves are currently under reconstruction and will be updated in the near future. Researchers

[57] First, there should be no omitted pre-treatment variables that determine the statistical link between the treatment variable on the outcome variable. (The same applies for the link between the mediator variable-here the economic variable- and the outcome variable). Second, there should be no intermediate interactions (Arachya et al. 2016).

will then have the opportunity to study longer periods at the sub-national level and to use more precise geo-information on the location of each respondent.[58]

In addition, future studies could explore in more detail to what extent expectations are based on the level of QoG. In this thesis, I have not clarified whether QoG influences social protest in a linear or curvilinear way. Hence, it could be the case that citizens' expectations on government's performance in the wake of natural disasters are shaped by the amount of public goods they receive during normal times. Assuming a curvilinear relationship, one could argue that citizens who are not accustomed to the provision of public goods because of a low level of QoG also do not expect help from the government in the wake of natural disasters. These people, therefore, will be unlikely to protest. Citizens might also not protest if they are used to a high amount of public good provision during normal times, because they will be particularly likely to receive the needed public goods during natural disasters. A high likelihood of social protest, then only arises at intermediate levels of QoG because the expectation-ability discrepancy will be the largest. When testing this theory, one could also investigate whether citizens' expectations vary across actors with different levels of education and occupation.

Lastly, the empirical validity of my theoretical argument is restricted to the region of Central America and the Caribbean. Therefore, future studies should apply my theoretical argument on natural disasters, QoG and social protest to other disaster-prone areas such as Sub-Sahara Africa or the Asia-Pacific region. The recently published geo-coded Afrobarometer data set (Afrobarometer 2017) at the sub-nation level represents an important achievement in that respect. The Afrobarometer data (Afrobarometer 2017) corresponds in many aspects to the survey design of the AmericasBarometer (LAPOP 2004-2014) and thus can be used to empirically assess the impact of QoG on social protest occurrence in the aftermath of natural disasters.

VII. Conclusion

Inspired by the ongoing-debate on the security risks of climate change, this thesis has dealt with the question how natural disasters are linked to social conflicts. The research field on the natural disaster-conflict nexus has provided divergent results on the statistical relationship between natural disasters and conflicts. One group of authors (Brancati 2007, Nel & Righarts 2008, Barron et al. 2009, Eastin 2016, Schleussner et al. 2016, Wood & Wright 2016) finds a positive association, whereas another group of authors (Bergholt & Lujala 2012, Slettebak 2012) claims that natural disasters are associated

[58] I obtained this information via e-mail from Rubi E Arana, who is the program and subscription Coordinator for the AmericasBarometer (LAPOP) at Vanderbildt University.

with less conflicts. Therefore, numerous authors (Goldstone et al. 2010, Raleigh & Urdal 2007, Buhaug et al. 2008, Enia 2009, Raleigh 2010, Omelicheva 2011, Adano et al. 2012, Quiroz Flores & Smith 2013, Detges 2016, Wig & Tollefsen 2016) propose that natural disasters only lead to conflicts under certain conditions. According to these authors, the institutional quality of the state is one of the core conditioning variables. Yet, the concept of QoG remains largely understudied. In order to address this gap, this thesis has put a special focus on the role of QoG in the wake of natural disasters.

By developing a new theoretical framework on natural disasters, QoG and social protest, this thesis shed light on the question why citizens protest in the aftermath of natural disasters. It thereby contributes to the vast bulk of literature on the climate-conflict nexus. Based on insights from public choice and relative deprivation theory, I proposed that citizens are more likely to protest in the wake of natural disasters if there is a lack of QoG. In addition, my theory suggested that high levels of QoG decrease the likelihood of social protests in the aftermath of natural disasters. The theoretical framework has global applicability and can therefore be tested empirically in other disaster-prone areas.

Moreover, I established a coherent link between my theoretical framework and my statistical analysis. For that purpose, I adapted my concept of conflicts to the very specifics of the post-disaster period. By using information on small-scale incidences of social conflicts, I addressed existing weaknesses in the literature that evolved because of misspecification of the conflict variable. In addition, by using single key features of QoG, instead of broad concepts of "good governance", I made notable efforts to capture the actual source of social grievances that, in the wake of natural disasters, motivate citizens to protest against the government.

In this thesis, I have focused on seven Central American and three Caribbean countries, which are particularly vulnerable to natural disasters but also characterized by varying levels of QoG. In order to be able to assess my theoretical framework in the context of Central America and the Caribbean, I created a new disaggregated data set for the period 2008-2015. By extending the geo-information of the AmericasBarometer (LAPOP 2008-2014) at municipality level, and by compiling several data sets with a fine spatial resolution, I faced the current need for data disaggregation in the research field. More importantly, the disaggregation of the data allowed me to explore the within-country variation. Thereby, I could overcome existing short-comings in the literature.

My findings of the logit models revealed that the sole occurrence of natural disasters hardly increase the likelihood of social protests. The QoG, on the contrary, turned out to be a significant predictor of social protests in the wake of natural disasters. I also found that the effect of natural disasters on social protest is particularly pronounced by the quality of the bureaucratic services. Even though my findings were robust among all model specifications, one must treat them with caution. In the discussion, I have noted that several biases could persist despite of my robustness checks. Thus, further research, is needed to consolidate both my theoretical model and my empirical findings.

Given that natural disasters will be much more frequent in the near future, the formulation of appropriate disaster policies is of paramount importance. My results indicate a tailored policy response: QoG matters in the wake of natural disasters. Social protests in consequence of natural disasters are an indication of a system with inherent problems of impartiality. Moreover, they indicate that people needlessly suffer from the lack of responsibility of their government. As a policy implication of my study, I certainly do not recommend that social protests should categorically be opposed in the aftermath of natural disasters. Social protests provide important outlets for citizens to express their opinions. In the wake of natural disasters, they can function as a wake-up call for governments and thereby lead to policies that better protect the population against future natural hazards. I rather advocate that QoG should be specifically promoted in disaster prone areas. The adoption of adequate disaster policies is a necessary but not sufficient condition for the protection of citizens. Hence, only if these policies are implemented by impartial state institutions, maximum protection is ensured. International donors, thus, should be aware of potential misappropriation of disaster relief aid in areas with low QoG.

My findings can also provide food for thought for the discussion on conflict prevention. Keeping in mind, that social protests are indicators of political violence and instabilities, they should, best be avoided. Even though participation in protests starts small-scale, it can, under certain conditions, lead to large-scale rebellions, high levels of violence and even civil war. Yet, by enhancing the QoG in disaster prone areas, social protests will become less likely and thus reduce the risk of long-term conflicts. Last but not least, my findings might also be of interest for theories on political transition and democratization because social protests can in extreme cases, lead to regime change.

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Appendix

TABLE A 1:
Number of Municipalities exposed to Disasters by Country and Type of Disaster (2008-2015)

Country	drought=0	**drought=1**	hurricane=0	**hurricane=1**	flood=0	**flood=1**
Costa Rica	500	**67**	567	**0**	504	**144**
Dom. Republic	1.044	**76**	932	**188**	623	**657**
El Salvador	1.551	**283**	1,834	**0**	1420	**676**
Guatemala	2.096	**249**	2,316	**29**	1826	**854**
Haiti	294	**0**	248	**46**	201	**135**
Honduras	1.838	**185**	1,981	**42**	1519	**793**
Jamaica	81	**10**	78	**13**	82	**22**
Mexico	11.683	**1.470**	12,317	**836**	10.975	**4.057**
Nicaragua	943	**114**	1,04	**17**	852	**356**
Panama	511	**28**	539	**0**	484	**132**
Total	20.541	**2.482**	21.852	**1.171**	18.486	**7.826**

TABLE A 2: Complementary Log-Log Regression Output for Main Effect

DV: Social Protest	**M 1**	**M 2**	**M 3**	**M 4**	**M 5**	**M 6**	**M 7**	**M 8**	**M 9**
Natural Disaster	0.277** (0.086)	0.245** (0.086)	0.247** (0.086)	0.233** (0.086)	0.287** (0.088)	0.298** (0.088)	0.189** (0.095)	0.155 (0.095)	0.212** (0.086)
Population Density (log)		0.160** (0.064)	0.205** (0.096)	0.285** (0.094)	0.467** (0.090)	0.439** (0.090)	0.446** (0.091)	0.352** (0.087)	0.368** (0.078)
Economic Development			-0.826 (1.316)	-1.985 (1.269)	-2.745** (1.280)	-3.740** (1.220)	-3.910** (1.270)	-2.436* (1.360)	-2.145** (0.929)
Ethnic Groups				-0.715** (0.167)	-0.641** (0.169)	-0.646** (0.169)	-0.662** (0.170)	-0.366** (0.179)	-0.611** (0.150)
Distance to Capital					0. 001** (0.000)	0. 001** (0.000)	0.001** (0.000)	0. 001** (0.000)	0. 001** (0.000)
Urban Share						0.096* (0.053)	0.098* (0.053)	0.100** (0.050)	0.071* (0.041)
country 0/1	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	Yes
N	26312	26312	26312	26312	26312	26312	26312	26312	26312

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$

TABLE A 3: Logit Regression Output for Main Effect with Disaster(t-1) and Disaster (t-2)

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10
Natural Disaster (t-1)	0.255** (0.091)		0.272** (0.092)		0.151 (0.102)		0.125 (0.106)		0.257** (0.115)	
Natural Disaster (t-2)		0.197** (0.082)		0.182** (0.083)		0.155* (0.089)		0.104 (0.092)		0.099 (0.115)
Population Density (log)			0.457** (0.096)	0.456** (0.096)	0.466** (0.097)	0.464** (0.097)	0.364** (0.092)	0.364** (0.092)	0 (.)	0 (.)
Economic Development			-3.911** (1.285)	-3.884** (1.288)	-4.085** (1.327)	-4.065** (1.326)	-2.570* (1.415)	-2.569* (1.418)	2.605 (2.038)	2.508 (2.045)
Ethnic Groups			-0.657** (0.171)	-0.660** (0.171)	-0.673** (0.171)	-0.670** (0.172)	-0.387** (0.178)	-0.389** (0.178)	-0.580 (0.448)	-0.585 (0.452)
Distance to Capital			0. 001** (0.000)	0. 001** (0.000)	0. 001** (0.000)	0.001** (0.000)	0. 001** (0.000)	0. 001** (0.000)	0.001 (0.001)	0.001 (0.001)
Urban Share			0.0994* (0.057)	0.0976* (0.057)	0.102* (0.057)	0.101* (0.057)	0.104* (0.053)	0.103* (0.053)	0 (.)	0 (.)
country 0/1	No	No	No	No	No	No	Yes	Yes	No	No
year 0/1	No	No	No	No	Yes	Yes	Yes	Yes	No	No
FE	No	No	No	No	No	No	No	No	2240	2240
N	26311	26310	26311	26310	26311	26310	26311	26310	26311	26310

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$.

TABLE A 4: Logit Regression Output for Main Effect with different Types of Disasters

DV: Social Protest	M 1	M 2	M3	M 4	M 5	M 6	M 7	M8	M 9	M10	M11	M12
Hurricane	0.765** (0.165)			0.663** (0.166)			0.403** (0.179)			0.316 (0.207)		
Drought (t-1)		0.166 (0.151)			0.121 (0.150)			0.208 (0.154)			0.239 (0.189)	
Flood			0.167* (0.094)			0.230** (0.094)			0.075 (0.100)			0.231* (0.123)
Population Density (log)				0.489** (0.098)	0.442** (0.095)	0.456** (0.095)	0.391** (0.092)	0.352** (0.094)	0.364** (0.092)	0 (.)	0 (.)	0 (.)
Economic Development				-3.862** (1.304)	-3.596** (1.354)	-3.939** (1.281)	-2.607* (1.406)	-2.332 (1.556)	-2.582* (1.413)	2.404 (2.230)	2.561 (2.167)	2.551 (2.036)
Ethnic Groups				-0.720** (0.176)	-0.665** (0.173)	-0.667** (0.171)	-0.417** (0.179)	-0.400** (0.180)	-0.393** (0.178)	-0.355 (0.468)	-0.553 (0.460)	-0.606 (0.450)
Distance to Capital				0.000** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	0.001** (0.000)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Urban Share				0.0939 (0.058)	0.0907 (0.059)	0.0994* (0.057)	0.101* (0.054)	0.0964* (0.056)	0.104* (0.053)	0 (.)	0 (.)	0 (.)
country 0/1	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No
year 0/1	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No
FE	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
N	23023	23023	26312	23023	23023	26312	23023	23023	26312	1806	1851	2240

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown.
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$.

TABLE A 5: Logit Regression Output for Main Effect, restricted to Mexico

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10
Natural Disaster	0.244**	0.223**	0.230**	0.233**	0.324**	0.236**	0.319**	0.183	0.183	0.378**
	(0.111)	(0.113)	(0.112)	(0.111)	(0.116)	(0.111)	(0.115)	(0.123)	(0.123)	(0.145)
Population Density (log)		0.0862					0.311**	0.318**	0.318**	0
		(0.066)					(0.080)	(0.081)	(0.081)	(.)
Economic Development			0.745				-3.013**	-3.177**	-3.177**	-0.361
			(0.966)				(1.518)	(1.559)	(1.559)	(2.124)
Ethnic Groups				-0.736**			-0.666**	-0.688**	-0.688**	-0.283
				(0.237)			(0.239)	(0.240)	(0.240)	(0.497)
Distance to Capital					0.001**		0.001**	0.001**	0.001**	0.001
					(0.000)		(0.000)	(0.000)	(0.000)	(0.001)
Urban Share						0.113**	0.117**	0.119**	0.119**	0
						(0.043)	(0.060)	(0.060)	(0.060)	(.)
country 0/1	No	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	Yes
N	15032	15032	15032	15032	15032	15032	15032	15032	15032	1440

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$.

TABLE A 6: Logit Regression Output for Main Effect, with Economic Variable (t-1)

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10
Natural Disaster	0.279**	0.248**	0.274**	0.271**	0.326**	0.273**	0.278**	0.179*	0.155	0.234**
	(0.087)	(0.087)	(0.087)	(0.087)	(0.088)	(0.087)	(0.089)	(0.096)	(0.098)	(0.115)
Population Density (log)		0.162**					0.451**	0.461**	0.369**	0
		(0.064)					(0.090)	(0.092)	(0.086)	(.)
Economic Development (t-1)			0.653				-4.033**	-4.180**	-2.799**	-0.198
			(0.922)				(1.243)	(1.269)	(1.292)	(1.373)
Ethnic Groups				-0.622**			-0.660**	-0.677**	-0.387**	-0.789*
				(0.172)			(0.170)	(0.171)	(0.179)	(0.442)
Distance to Capital					0.000**		0.001**	0.001**	0.001**	0.001
					(0.000)		(0.000)	(0.000)	(0.000)	(0.001)
Urban Share						0.113**	0.0981*	0.102*	0.107**	0
						(0.042)	(0.057)	(0.057)	(0.053)	(.)
country 0/1	No	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	Yes
N	26312	26312	26311	26312	26312	26312	26311	26311	26311	2240

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$.

TABLE A 7: Logit Regression Output for Moderator Effect with QoG (t-2)

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11	M 12
Natural Disaster	0.428**	0.423**	0.387**	0.349**	0.371**	0.391**	0.413**	0.382**	0.392**	0.241	0.158	0.453**
	(0.130)	(0.130)	(0.132)	(0.133)	(0.133)	(0.133)	(0.135)	(0.133)	(0.138)	(0.147)	(0.151)	(0.227)
QoG-Index (t-2)		-0.376**	-0.292**	-0.257**	-0.286**	-0.286**	-0.302**	-0.286**	-0.258**	-0.285**	0.008	0.217
		(0.111)	(0.129)	(0.129)	(0.133)	(0.131)	(0.126)	(0.131)	(0.119)	(0.122)	(0.123)	(0.186)
Natural Disaster # QoG-Index (t-2)			-0.182	-0.164	-0.163	-0.173	-0.181	-0.174	-0.137	-0.113	-0.166	-0.285
			(0.141)	(0.142)	(0.144)	(0.141)	(0.139)	(0.142)	(0.137)	(0.139)	(0.139)	(0.236)
Population Density (log)				0.296**					0.631**	0.620**	0.618**	0
				(0.099)					(0.188)	(0.200)	(0.231)	(.)
Economic Development					1.767*				-2.077	-2.108	-1.966	2.849
					(1.024)				(1.600)	(1.762)	(2.006)	(4.750)
Ethnic Groups						-0.537*			-0.589**	-0.605**	-0.118	2.123*
						(0.291)			(0.287)	(0.292)	(0.277)	(1.232)
Distance to Capital							0.005**		0.001**	0.001**	0.001**	-0.019
							(0.000)		(0.000)	(0.000)	(0.000)	(0.014)
Urban Share								0.0642	-0.0541	-0.0562	-0.0560	0
								(0.044)	(0.071)	(0.074)	(0.066)	(.)
country 0/1	No	No	No	No	No	No	No	No	No	Yes	No	No
year 0/1	No	No	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	No	No	Yes
N	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	496

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$.

TABLE A 8: Logit Regression Output for Moderator Effect with QoG (t-2) and disaster (t-1)

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11	M 12
Natural Disaster (t-1)	0.393**	0.383**	0.386**	0.341**	0.374**	0.393**	0.418**	0.382**	0.397**	0.184	0.223	0.420*
	(0.148)	(0.149)	(0.149)	(0.153)	(0.150)	(0.149)	(0.150)	(0.149)	(0.155)	(0.179)	(0.184)	(0.226)
QoG-Index (t-2)		-0.374**	-0.383**	-0.350**	-0.377**	-0.373**	-0.389**	-0.373**	-0.342**	-0.357**	-0.054	0.098
		(0.111)	(0.141)	(0.141)	(0.145)	(0.144)	(0.139)	(0.144)	(0.129)	(0.129)	(0.123)	(0.192)
Natural Disaster (t-1) #QoG-Index (t-2)			0.0175	0.0409	0.036	0.015	0.0117	0.018	0.0477	0.0394	-0.024	-0.033
			(0.149)	(0.149)	(0.149)	(0.149)	(0.147)	(0.150)	(0.139)	(0.143)	(0.139)	(0.225)
Population Density (log)				0.298**					0.632**	0.626**	0.627**	0
				(0.099)					(0.189)	(0.203)	(0.231)	(.)
Economic Development					1.838*				-1.974	-2.045	-1.950	2.467
					(1.02)				(1.598)	(1.760)	(2.025)	(4.672)
Ethnic Groups						-0.545*			-0.596**	-0.612**	-0.115	2.279*
						(0.292)			(0.288)	(0.292)	(0.277)	(1.23)
Distance to Capital							0.000**		0.001**	0.001**	0.001**	-0.013
							(0.000)		(0.000)	(0.000)	(0.000)	(0.012)
Urban Share								0.066	-0.0569	-0.0593	-0.057	0
								(0.044)	(0.072)	(0.074)	(0.066)	(.)
country 0/1	No	No	No	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	No	No	Yes
N	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	4214	496

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown. * $p < 0.10$, ** $p < 0.05$.

TABLE A 9: Logit Regression Output for Moderator Effect with Representative QoG-Data (2013-15)

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11
Natural Disaster	-0.0199 (0.251)	-0.0222 (0.250)	-0.158 (0.266)	-0.112 (0.275)	-0.168 (0.267)	-0.169 (0.267)	-0.172 (0.265)	-0.158 (0.268)	-0.138 (0.275)	-0.111 (0.300)	-0.073 (0.301)
QoG-Index		-0.346** (0.111)	-0.223* (0.115)	-0.188 (0.118)	-0.228** (0.115)	-0.212* (0.116)	-0.252** (0.113)	-0.223* (0.116)	-0.185 (0.122)	-0.180 (0.123)	-0.173 (0.149)
Natural Disaster # QoG-Index			-0.452** (0.198)	-0.456** (0.203)	-0.444** (0.197)	-0.465** (0.199)	-0.424** (0.192)	- 0.452** (0.198)	-0.376* (0.196)	-0.393* (0.214)	-0.420* (0.230)
Population Density (log)				0.151 (0.127)					0.479** (0.222)	0.479** (0.221)	0.833** (0.310)
Economic Development					-0.626 (1.394)				-3.518 (2.351)	-3.501 (2.337)	-5.402 (3.557)
Ethnic Groups						-0.322 (0.359)			-0.337 (0.362)	-0.337 (0.362)	-0.168 (0.367)
Distance to Capital							0.001 (0.000)		0.001** (0.000)	0.001** (0.000)	0. 001** (0.000)
Urban Share								-0.000 (0.049)	-0.058 (0.075)	-0.059 (0.075)	-0.117 (0.083)
country 0/1	No	No	No	No	No	No	No	No	No	Yes	No
year 0/1	No	No	No	No	No	No	No	No	Yes	Yes	No
FE	No	No	No	No	No	No	No	No	No	No	Yes
N	1904	1904	1904	1904	1904	1904	1904	1904	1904	1904	1904

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown.
* $p < 0.10$, ** $p < 0.05$.

TABLE A 10: Logit Regression Output for Moderator Effect restricted to Mexico

DV: Social Protest	**M 1**	**M 2**	**M 3**	**M 4**	**M5**	**M 6**	**M 7**	**M 8**	**M9**	**M 10**	**M 11**
Natural Disaster	0.494*	0.471*	0.420	0.413	0.418	0.422	0.496*	0.413	0.575**	0.325	0.870**
	(0.261)	(0.260)	(0.267)	(0.265)	(0.264)	(0.267)	(0.260)	(0.260)	(0.267)	(0.272)	(0.394)
QoG-Index		-0.134	-0.0296	-0.0109	-0.0279	-0.0413	-0.137	-0.0253	-0.134	-0.112	0.0610
		(0.118)	(0.141)	(0.143)	(0.143)	(0.139)	(0.150)	(0.143)	(0.151)	(0.154)	(0.232)
Natural Disaster # QoG-Index			-0.229	-0.221	-0.228	-0.235	-0.195	-0.229	-0.169	-0.148	-0.406
			(0.188)	(0.193)	(0.193)	(0.192)	(0.184)	(0.189)	(0.201)	(0.207)	(0.346)
Population Density (log)				0.0802					0.413**	0.472**	0
				(0.094)					(0.150)	(0.161)	(.)
Economic Development					0.0946				-2.058	-2.583	-17.41**
					(1.358)				(2.403)	(2.557)	(8.339)
Ethnic Groups						-0.366			-0.211	-0.320	-0.587
						(0.490)			(0.502)	(0.500)	(1.266)
Distance to Capital							0.001**		0.001**	0.001**	0.002
							(0.000)		(0.000)	(0.000)	(0.002)
Urban Share								0.0159	-0.0337	-0.0423	0
								(0.051)	(0.079)	(0.080)	(.)
year 0/1	No	No	No	No	No	No	No	No	No	Yes	No
FE	No	No	No	No	No	No	No	No	No	No	Yes
N	1012	1012	1012	1012	1012	1012	1012	1012	1012	1012	208

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown.
* $p < 0.10$, ** $p < 0.05$.

TABLE A 11: Logit Regression Output for Moderator Effects with separate QoG-Indicators

DV: Social Protest	M 1	M 2	M 3	M 4	M 5	M 6	M 7	M 8	M 9	M 10	M 11	M 12
Natural Disaster	0.415**	0.407**	0.406**	0.391**	0.400**	0.347**	0.294*	0.285*	0.190	0.298	0.341*	0.216
	(0.133)	(0.136)	(0.136)	(0.135)	(0.138)	(0.137)	(0.157)	(0.159)	(0.157)	(0.207)	(0.206)	(0.215)
Municipality Service	-0.223			0.0703			0.361			0.0998		
	(0.202)			(0.244)			(0.223)			(0.315)		
Rule of Law		-0.733**			-0.687**			-0.648**			-0.292	
		(0.149)			(0.187)			(0.205)			(0.371)	
Low Corruption			-0.904**			-0.706**			0.0603			0.405
			(0.139)			(0.172)			(0.212)			(0.296)
Natural Disaster # Municipality Service				-0.559**			-0.286			-0.616		
				(0.269)			(0.244)			(0.400)		
Natural Disaster # Rule of Law					-0.0870			0.0514			-0.265	
					(0.254)			(0.277)			(0.507)	
Natural Disaster # Low Corruption						-0.380*			-0.610**			-0.762**
						(0.201)			(0.236)			(0.382)
Population Density (log)							0.852**	0.860**	0.862**	0	0	0
							(0.225)	(0.223)	(0.225)	(.)	(.)	(.)
Economic Development							-4.516*	-4.719*	-4.522*	-7.225*	-7.315*	-6.627
							(2.507)	(2.667)	(2.515)	(4.308)	(4.307)	(4.236)
Ethnic Groups							-0.0349	-0.0340	-0.0305	-1.727	-1.785	-1.584
							(0.281)	(0.280)	(0.280)	(1.106)	(1.116)	(1.074)
Distance to Capital							0.009**	0.000**	0.000**	0.000	0.000	0.000
							(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Urban Share							-0.072	-0.067	-0.070	0	0	0
							(0.081)	(0.082)	(0.079)	(.)	(.)	(.)
country 0/1	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No
year 0/1	No	No	No	No	No	No	Yes	Yes	Yes	No	No	No
FE	No	No	No	No	No	No	No	No	No	Yes	No	Yes
N	4214	4214	4214	4214	4214	4214	4214	4214	4214	622	622	622

Robust standard errors in parentheses clustered on municipality. Some estimations include year and country dummies, results not shown.
* $p < 0.10$, ** $p < 0.05$.