Natural Disasters and Frequency: Effects on Political Trust

In Central America, Mexico and Colombia

Frank By Estenstad & Ingvild Skagestad

Supervisor: Po Yin Wong
MSc in Economics and Business Administration
Major in Energy, Natural Resources and the Environment
Norwegian School of Economics
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Frank By Estenstad

Ingvild Skagestad

Abstract

In recent decades, natural disaster frequency and magnitude have been steadily increasing, while climate change continues to be a topic mixed with facts and opinions. The vast majority of researchers are in consensus that climate change is happening and that one of the direct consequences are extreme weather events. Still, few things are as divisive politically as the discussion of climate change and the possible, if not plausible, effects. This begs the question; how does this affect the general population's trust towards politicians, political parties and governments? What happens to political trust?

To investigate this, we have constructed a fixed effects model at province level over 6 study periods from 2004-2014. 243 natural disasters affecting 132 different provinces over 8 countries were analyzed with the aim to investigate if weather-related natural disasters and natural disaster frequency have an impact on political trust in Central America, Mexico and Colombia. This is one of the very few studies that uses panel data to investigate multiple disasters in several countries over a number of years, instead of focusing on single disaster events like most of the current literature on natural disasters and political trust. Although no statistically significant general effects on political trust were found in this study, a potential weak positive effect when frequency is low, and a weak negative effect when frequency is high as opposed to no disaster event, was found.

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1 Introduction

The frequency of weather-related natural disasters is increasing over time, while natural disaster fatality rates are decreasing (The Economist, 2017). Since the beginning of the 20th century, more than 35,000 natural disasters have killed over 8 million people, corresponding to an economic cost of 7 trillion USD (Karlsruhe Institute of Technology, 2016). In 2017, the number of reported natural disasters in the world was 335, causing 96 million people to be affected (CRED, 2018a). As the frequency of natural disasters increases, it necessitates a better understanding of the potential challenges the world will face in the future.

Natural disasters are political events as well as social, and the government and politicians are often held responsible for the consequences after a disaster. The disaster event in itself is exogenous to politics (at least as a direct consequence), but how well the politicians are prepared in advance and how they manage the disaster can be seen as a political matter. Therefore, how politicians handle the aftermath of a natural disaster can potentially be expected to either weaken or strengthen their political position. One way of testing this hypothesis is to explore changes in political trust in the aftermath of natural disasters. This study investigates if weather-related natural disasters, and their level of frequency, can affect political trust.

There is a substantial amount of empirical literature studying natural disasters, but most economic studies are looking at macroeconomic consequences after natural disasters, often estimating gross domestic product (GDP) losses or changes in annual growth (Kousky, 2004). Both natural disasters and political trust are topics with increasing interest among scholars, but the relationship between the two has only been investigated to a small extent. Prior literature is mainly focusing on single disaster events and country specific analyses (Albrecht, 2017a). This thesis, however, focuses on several countries, capturing different disaster events over a longer period of time. This allows us to look at the long-term general, not singular, effects from weather-related natural disasters. It also makes it possible to study effects of natural disaster frequency.

The aim of this study is to systematically investigate if prior empirical results can be externally valid at a more general level. This thesis will study natural disasters in Central America, Mexico and Colombia. More precisely, this includes Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama, Mexico and Colombia. Our geographical choice is based on the frequent number of weather-related natural disasters that occurs in this specific region (EM-DAT, 2018). This is of particular interest considering the consensus among researchers that weather-related natural disasters are connected to climate change, and that these disasters will be more frequent if the change in climate continues on its current path (The Earth Observatory, 2005). Another interesting aspect of the choice of region is that even though Asia had 44 percent of the natural disaster events in 2017, the highest economic losses were in the Americas (CRED, 2018a). Nevertheless, one should be critical of comparisons across countries, as cost may differ when controlling for factors like GDP and relative costs between countries.

Based on the information provided in the first part of the introduction, we have chosen to divide the research question into two hypotheses. First, we want to investigate if weather-related natural disasters have long-term effects on political trust in the region of interest. In this research we define political trust as trust in political parties. A deeper understanding of the definition will be elaborated in section 2.1.2 of this thesis. Second, we will look at disaster frequency, and study if changes in frequency matter for political trust. The choice of time perspective is based on the fact that there is a higher chance to detect potential effects on political trust in the long than in the short run. However, current literature says if no significant results are discovered within the first couple of months after a disaster, no later effects are likely to be found either (Albrecht, 2017a). We define the long run to a time period of four years, which in many countries corresponds to a presidential term of office. It is a period of time where one usually see significant changes in the political scene, thus we find the definition reasonable for our study. The first hypothesis is presented below.

H_1: *Weather-related natural disasters have little effect on political trust in the long run.*

The first hypothesis is based on the assumption that natural disasters are of political relevance because people relate political trust to the performance of the politicians, in our case how political parties manage disaster events. Whether politicians handle the aftermaths of a disaster in a good or bad way may affect the perception of the political performance, and as follows be related to political trust. A high level of political trust might indicate that the citizens have confidence in the politicians being capable of managing a natural disaster. Based on former empirical evidence, there is uncertainty about what to expect from the first hypothesis. Most studies have found that natural disasters do have a political effect, but to what degree is uncertain. This is further elaborated in the literature review in section 2.2. As most previous research has identified both negative and positive changes in political trust following a natural disaster, we would expect natural disasters to have an impact on political trust in this analysis as well. However, Albrecht (2017a), one of the few studies investigating political trust over several disasters in different countries, found weak evidence of natural disasters having an effect on political trust. The study concluded that prior research often tends to overestimate the effects on political trust following a natural disaster. As this is a somewhat similar approach as the study at hand, using cross-country data, we can therefore assume to find weak evidence of a change in political trust in this study. The second hypothesis will now be presented.

H_2: *Higher frequency of weather-related natural disasters has a negative impact on political trust.*

In the second hypothesis we study if the frequency of weather-related natural disasters has an effect on political trust. This is interesting as the number of weather-related natural disasters is increasing. To our knowledge, there are up to this date conducted no studies investigating if natural disaster frequency matters for political trust. Expected findings are therefore uncertain. Nevertheless, there is a wide scientific agreement that weather-related natural disasters are connected to climate change (ECIU, 2017). Climate change is a political matter, with many different opinions and thoughts related to the issue. The inhabitants in a country might be more aware of climate change and relate the issue to be a political one if the natural disaster frequency in the country increases. This could raise questions on whether politicians could have prevented the occurrence of a natural disaster with better climate change mitigation, and therefore a potential change in trust could be seen. We expect findings indicating that natural disaster frequency have some significant impact on political trust.

1.1 Thesis Outline

The outline of this thesis will be as follows. Section 2 will introduce the background information on the topic, including terminology about natural disasters and political trust, as well as presenting relevant literature on the topic. Section 3 gives an overview of data used in this thesis, including data limitations and data modifications. The empirical strategy will be introduced in section 4, and the empirical analysis and findings are provided in section 5. Section 6 presents robustness checks, followed by a discussion of results and policy implications in section 7. At last, we conclude in section 8.

2 Background Information

2.1 Terminology

2.1.1 Natural Disasters

Henceforth we use the definitions on natural disasters from the Centre of Research on the Epidemiology of Disasters (CRED, 2018b).

First, it is important to be aware of the difference between natural disasters and natural hazards. Natural hazard is defined as a threatening event, or the possibility of a potential harmful phenomenon in a given time and region. A natural disaster, on the other hand, is an episode or event that is overwhelming at the local level, where external support is required. Additionally, it can be defined as an unexpected event with grave damage and consequences including human suffering. CRED divides natural disasters into 6 different subgroups; geophysical, hydrological, meteorological, climatological, biological, and extraterrestrial. Today, most researchers agree that human activity acts as a catalyst for climate change and is affecting weather-related natural disasters (Faust & Höppe, 2017). Climate change can influence both the frequency and the intensity of these disasters. EM-DAT defines weather-related natural disasters as hydrological, meteorological, and climatological natural disasters. Their corresponding disaster types are specified in Table T.1. Since there is no clear evidence that climate change affects geophysical disasters, such as volcanic activity and earthquakes (Faust & Höppe, 2017), nor extraterrestrial disasters, we limit this thesis to only include weather-related natural disasters. Note that even if wave action, fog and glacial lake outburst are classified in the disaster subgroups we are looking at, no such disaster events are recorded in our data set.

Table T.1: Weather-Related Natural Disaster Subgroups (EM-DAT, 2018)

Disaster Subgroup	**Type of Disasters**
Hydrological	Flood, Landslide, and Wave Action
Meteorological	Extreme Temperature, Fog, and Storm
Climatological	Glacial Lake Outburst, Drought, and Wildfire

2.1.2 Political Trust

We can define political trust in several ways, for instance by trust in political parties, political institutions or the government. Due to different opinions about the concept of political trust, the theory and perception of political trust differ (Uslaner, 2018). Thus, scholars argue if political trust empirically is one-dimensional or has several dimensions (Hooghe, 2011; Fisher, Van Heerde, & Tucker, 2010; Rothstein & Stolle, 2008). For instance, Fisher et al. (2010) did find variation in the different forms of political trust. However, this distinction of the concept of political trust is discussed to be more relevant in theory and not that relevant empirically (Hooghe, 2011). For the purpose of this study, we will measure and define political trust as trust in political parties. More specifically, this includes the degree of which political performance is evaluated relative to how they are expected to perform, hence the perception of political action and performance (Coleman, 1990; Hetherington, 2005; Miller, 1974; Stokes, 1962; Hetherington & Husser, 2012). In this case, the general public opinions and perceptions are essential (Bovens & Hart, 2016; McConnell, 2015). For instance, according to Uslaner (2016), trust in government depends on how fast and satisfactory a government reacts after a natural disaster occurs. Nevertheless, there might not be a clear indication to what extent the performance is successful or not (Albrecht, 2017a).

2.2 Literature Review

This section will present the relevant research on natural disasters and political trust to provide the reader with a better understanding of the relationship between this study and previous literature. We have divided the literature review into two parts. First, we present a summary of the most relevant research on the economics of natural disasters. This is relevant to our study, as we are investigating political factors with an economic perspective. Second, we will give an overview of the already existing empirical literature on natural disasters and the effects on political trust.

2.2.1 Economics of Natural Disasters

Studies on the economics of natural disasters are often divided into three classifications: 1) Aspects that can affect the severity of the externalities following a natural disaster; 2) short-term economic effects of natural disasters; and 3) long-term social aspects of living in an area exposed to disasters (Toya & Skidmore, 2012). This section will be based on these classifications.

We start with the first classification about disaster vulnerability and factors that influence it. As this is commonly studied, our thesis will not investigate this further. Nevertheless, how vulnerable a society confronting natural disasters is, depends on several economic, social and political aspects. Researchers have found evidence that disaster vulnerability decreases when income is rising (Toya & Skidmore, 2012), indicating that poorer countries are more vulnerable to disasters. This is interesting with respect to our study, as Central America is considered to be the poorest region in Latin America (The Tico Times, 2013). Despite the fact that poor nations do not experience a higher frequency of natural disasters than richer countries, the consequences are often more severe in poor countries (Kahn, 2005). Much of this is explained by institutions and inequality, as Kahn (2005) found that more stable institutions, more democratic countries and more equality decrease disaster vulnerability.

In the long run, scholars have identified long-lasting negative consequences on economic activity after a disaster strikes (Cavallo et al., 2009; McDermott, 2011). Our study does not investigate economic activity directly. However, politics and the economy are strongly tied together, and a change in the perception or trust towards politicians can, according to Fukuyama (1995), create a stronger and more stable economy. Regarding the economic perspective, several studies have been conducted looking at short-term economic consequences. Research on the effects on GDP often differs in the results, depending on the specific country or disaster event (Kousky, 2004). However, much research suggests that GDP has a tendency to increase after a disaster (Albala-Bertrand, 1993; Otero & Marti, 1995), while economic growth tends to decrease, especially following large disasters (Raddatz, 2005; Noy, 2009; Raddatz, 2009; Loayza, E. Olaberría, & Christians, 2009; Fomby, Ikeda, & Loayza, 2009; Hochrainer, 2009).

According to Toya and Skidmore (2012), only two papers are written about the last classification on the effects of living in an area with higher risk of natural disaster occurrences. Findings show that areas that are more vulnerable to natural disasters have a positive effect on human capital, economic growth and factor productivity after a disaster strikes (Toya & Skidmore, 2002; 2012). Thus, regions seem to be better prepared for disasters when knowing they are more exposed to them. Central America, Mexico and Colombia are relatively vulnerable to natural disasters, and can therefore be expected to be better prepared than less vulnerable countries according to the findings elaborated above. In the future, population growth and climate change are plausible critical factors increasing human vulnerability to natural disasters (Carlin, Love, & Zechmeister, 2014). Population growth is relevant due to increased population density and settlements in more risk exposed regions (Strömberg, 2007).

2.2.2 Empirical Evidence of Natural Disasters on Political Trust

The following section will give an overview of the existing literature on natural disasters and the effects on political trust. Trust is often divided into societal trust and political trust (Uslaner, 2018). Societal trust is argued to mostly be direct and primary experience with others, while political trust is said to be experienced indirectly at a distance, often through the media (Newton, 2001). Prior studies on societal trust have varied results, and empirical evidence has shown both positive, negative and no consequences on societal trust after the occurrence of a natural disaster (Cassar, Healy, & von Kessler, 2017; Castillo & Carter, 2011; Yamamura, 2016; Papanikolaou et al., 2012; Uslaner, 2016). That said, the two types of trust are often found to have weak correlation with each other (Uslaner, 2016). Societal trust will not be further elaborated as this study will only focus on political trust. So why does political trust matter? Some researchers argue that a decrease in trust is not of much importance, while others have opposite opinions (Citrin, 1974; Citrin & Green, 1986; Fukuyama, 1995). Fukuyama (1995) claims that trust can encourage a more stable and collaborative society, trigger a more democratic government, and strengthen the economy. In addition, a population with high level of trust leads to more political stability and better performance (Nicholls & Picou, 2012). As many scholars before us, we base this study on the assumption that political trust does matter, much due to the argumentation from Fukuyama (1995) and Nicholls & Picou (2012) mentioned above.

There are different opinions on whether trust can be influenced in the short run, or if trust is actually more stable over time and therefore will not be affected by short-term external factors (Miller, 1974; Citrin, 1974; Citrin & Green, 1986; Hetherington, 1998; Hetherington & Husser, 2012). In this study, we assume that political trust can change in the short term by external events, in this case by natural disasters. Nevertheless, research that is based on this assumption also tends to look at changes in the long run, which is of greater relevance to this study. As stated earlier, our definition of political trust focuses on the perception of political action and performance. When a natural disaster strikes, the inhabitants are in need of public help and assistance. The expectations towards leaders are high, and the trust can increase if the authorities have good disaster management. On the contrary, if the public offices do not live up to their expectations, the confidence in them can fall (Uslaner & Yamamura, 2016). This could especially be the case if the politicians could have implemented better risk management before a natural disaster to reduce the externalities related to them.

Assuming that weather-related natural disasters influence individual opinions and perception of political performance, it is relevant to point out that the perception of political performance can be measured in different ways (Powell, 1982). On the one hand, scholars have looked at long-run trends of the population's satisfaction or confidence in the democracy and the political system (Carlin et al., 2014). On the other hand, political performance has been measured as individual opinions on governmental and political actors, such as confidence or trust with the government (Albrecht, 2017a). This research is based on the latter, where the the survey from LAPOP captures individual perception of trust in political parties as measurement of political trust.

Another way of measuring political performance is by looking at voter turnouts in elections in the aftermaths of a disaster (Arceneaux & Stein, 2006; Bechtel & Hainmueller, 2011; Cole, Healy, & Werker, 2012; Debbage et al., 2014; Eriksson, 2016; Gasper & Reeves, 2011; Healy & Malhotra, 2010; Velez & Martin, 2013). This study does not measure political trust with voter turnouts as natural disasters can be seen as random events, thus the timing of the event and the distance in time to a election will vary when a disaster strikes. Therefore, there might not be data on the voter turnouts before and after a natural disaster, hence the treatment effect of the disaster can be difficult to measure. In general, natural disasters can be seen as "fast-burning crises", indicating that a disaster has short-lasting effects (Boin & t Hart, 2001; Boin, McConnell, & ‘t Hart, 2008; Houston, Pfefferbaum, & Rosenholtz, 2012; Kruke & Morsut, 2015). To capture short-term effects can be difficult, as there might be a lack of available data shortly before and after a disaster. Albrecht (2017a) avoids this issue by choosing 10 cases of natural disasters in Europe using a quasi-experimental approach. The cases are carefully elected based on available interview data both before and after the disasters. This approach is in contrast to our study, where we have chosen to use survey data over 6 panels, capturing several hundred disaster events.

Most research on natural disasters and political trust are conducted within countries and are single disaster-specific. Former studies show that natural disasters often have a negative political impact after an event, and that they tend to decrease support in the democracy and its values (Carlin et al., 2014; Akbar & Aldrich, 2015). Research after the earthquake and the subsequent tsunami in Japan in 2011 gives indications that trust in government was dropping (Uslaner, 2016; Uslaner & Yamamura, 2016), and a similar effect on local government was found in the 2008 Wenchuan earthquake in China (Han, Hu, & Nigg, 2011). Additionally, there was a decrease of political trust and trust in the government after Hurricane Katrina in the United States of America in 2005, due to lack of ex ante preparation and ex post management (Forgette, King, & Dettrey, 2008; Nicholls & Picou, 2012; Parker et al., 2009). Despite this, there are also natural disasters with an increasing effect on political trust, such as in Germany after a flood in 2002 (Bechtel & Hainmueller, 2011) and more trust in the national government in China after an earthquake in 2008 (Han et al., 2011). Nonetheless, former studies have a tendency to analyze unique disaster events, and one should be careful when applying these results in general, as the effects are likely to be more amplified compared to ordinary disasters (Albrecht, 2017a).

Previous research tends to have found evidence of a change in political trust following a natural disaster, whereas Albrecht (2017a) found little evidence of political trust being affected by it. Her research concluded that prior studies have a tendency to overestimate the effects after a disaster event, and that results from previous research should in general not be applied. She reasons that political trust is relatively stable over time, and that politicians are not often blamed for the consequences following natural disasters. Scholars have argued that some of the reasons for the overestimation of prior research might be due to media coverage (Boin, McConnell, & Hart, 2009; Brändström, Kulpers, & Daléus, 2008; Bytzek, 2008). The media tends to provide extra coverage when it concerns disasters, both during and a short time after the event occurs, which might influence the understanding of how the public opinion of politicians actually is.

Overall, the results from the existing literature on natural disasters and political trust vary, and there exist a current need for more studies to be conducted on the topic. An increase in studies can contribute to a better understanding of the determinants and consequences of natural disasters, something that is relevant as weather-related natural disasters are becoming more frequent. Additionally, it can help politicians and governments to obtain a better understanding of the issue and provide politicians and leaders with more knowledge on how to gain the trust of their citizens (Fisher et al., 2010).

3 Data

3.1 Data on Natural Disasters

Data on natural disasters are collected from the International Disaster Database (EM-DAT) supported by The Centre for Research on the Epidemiology of Disaster (CRED) at the University of Louvain in Brussels, Belgium. EM-DAT is a public cross-country database that obtains data from different sources such as UN agencies, insurance companies, non-governmental organizations, the press, and research institutes (CRED, 2018c). There are certain criteria to be fulfilled for a disaster to be included in the EM-DAT database. At least one of the following criteria has to be satisfied in order to be categorized as a disaster: There has to be reported ten or more deaths; hundred or more people have to be reported affected; the government has to declare a state of emergency and international assistance has to be requested by the government (CRED, 2018c). Specifically, EM-DAT provides data about frequency, disaster type, deaths, affected, economic damage, disaster magnitude, and duration. Data sets can be automatically compiled on the country level, but have to be manually extracted at lower levels like province and district.

Natural disaster frequency varies by country, and each disaster affects a different number of provinces as it strikes. Figure F.1 shows the frequency of natural disasters by country over our time period, and Figure F.2 shows the sum of provinces affected. Note that a province can be affected by multiple natural disasters in each year.

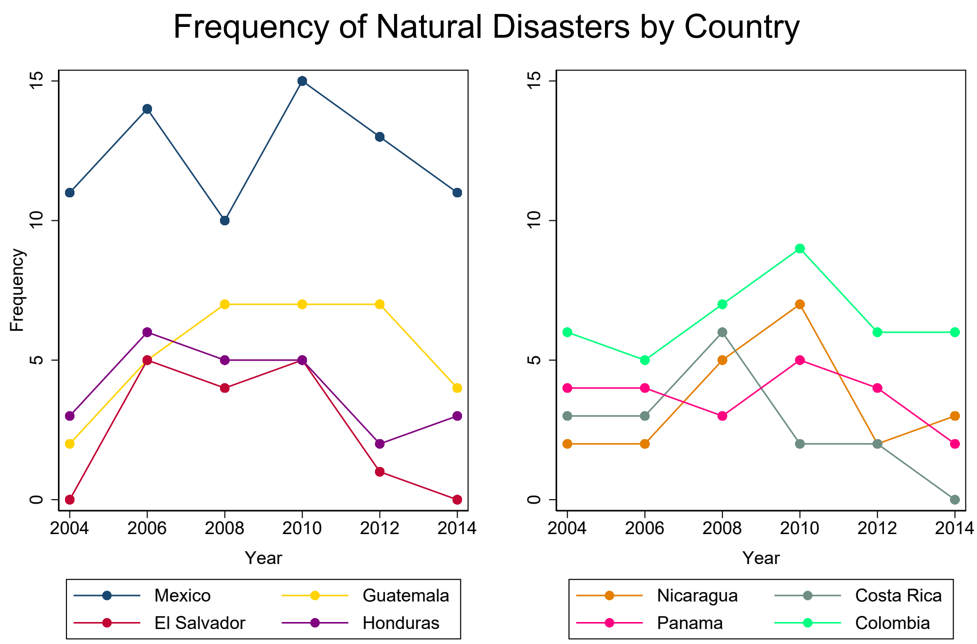

Figure F.1: Disaster Frequency by Country (EM-DAT, 2018)

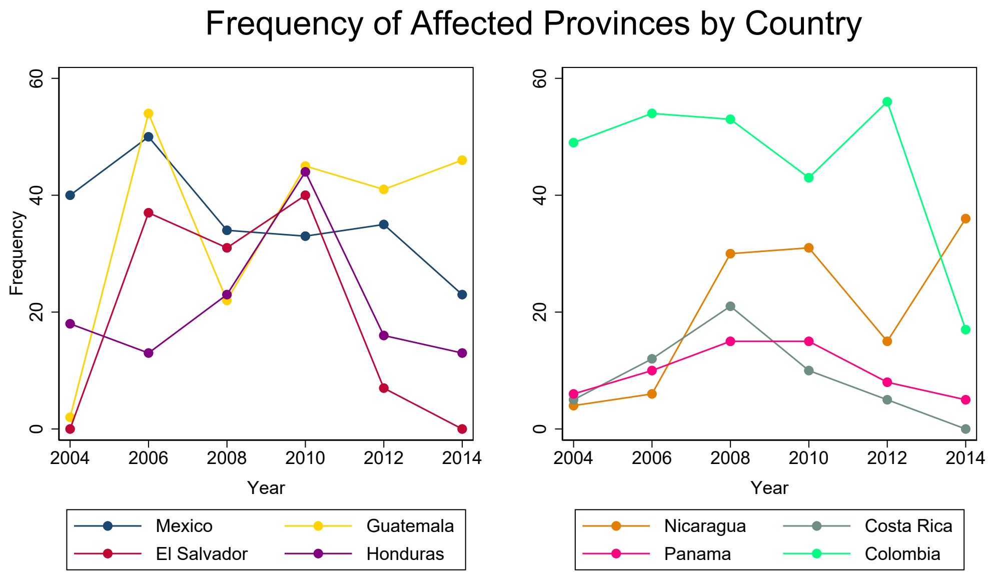

Figure F.2 shows the amount of provinces affected by natural disasters per country. Each province may be affected by multiple different natural disasters through a study period, so the frequency shown is notably higher than Figure F.1.

Figure F.2: Disaster Frequency by Province (EM-DAT, 2018)

From our sample, we divide weather-related natural disasters into the three different subgroups - hydrological, meteorological, and climatological - grouped by EM-DAT to control for different effects between the disaster classifications. The spread of the subgroups can be seen in Table F.3. Clearly, natural disasters of the hydrological subgroup dominate, followed by meteorological, and then climatological natural disasters.

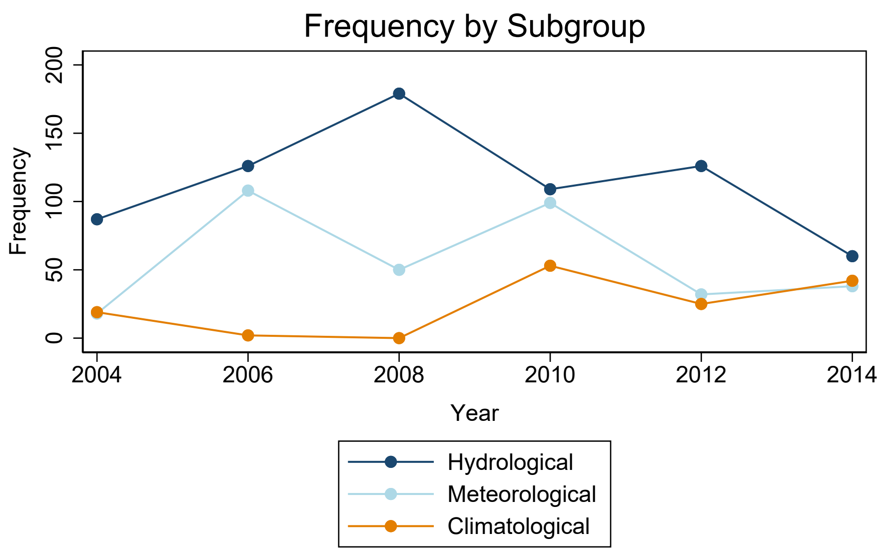

Figure F.3 shows the amount of provinces affected by natural disasters per country. Each province may be affected by multiple different natural disasters through a study period.

Figure F.3: Disaster Frequency by Subgroup (EM-DAT, 2018)

3.2 EM-DAT Limitations

The availability and quality of the EM-DAT data makes it the most popular database to use in studies on natural disasters (CRED, 2018c). Nevertheless, there are certain concerns related to the database. First, one potential issue is connected to the reporting of the disaster events. The process of reporting and misreporting varies across time and country, where the quality of reporting is plausible to have increased in recent years and in more developed countries (Strömberg, 2007). This may cause our estimates to be under- or overestimated. Additionally, smaller events might not be reported, although they still can have grave economic consequences (Kousky, 2004). In a report from The United Nations Office for Disaster Risk Reduction (UNISDR) from 2013, the UN reported that EM-DAT underestimates the direct economic losses in low- and middle-income countries by 50 percent (UNISDR, 2013).

Additionally, data on economic damage and total deaths are not always reliable in the EM-DAT database. This is for instance due to missing data (Toya & Skidmore, 2012). Another interesting reason is that some developing countries overestimate the economic costs following a disaster in order to receive more foreign support and aid (Albala-Bertrand, 1993). The fact that total economic losses often rise with income, indicates that we might have issues with endogeneity (Toya & Skidmore, 2012), which we try to correct for by adding a GDP per capita variable to our model. Nevertheless, the CRED database is considered the best available source for natural disasters (Kousky, 2004; Strömberg, 2007), and should therefore be used having the above concerns in mind.

3.3 Data on Political Trust and Control Variables

Data on public opinions in Central America, Mexico and Colombia are gathered from the survey AmericasBarometer from The Latin American Public Opinion Project (LAPOP), a research institute at Vanderbilt University in Nashville, Tennessee. LAPOP is the only provider of value surveys for democratic value opinions and behavior that offers data from all the Americas; from North, South, and Central America, as well as the Caribbean (LAPOP, 2018a). LAPOP has pooled cross sectional data, with surveys conducted every second year (LAPOP, 2016). The data currently available to us from LAPOP have been a restricting factor when choosing our study and time period. We were able to acquire a merged data set for our region from 2004 to 2014 with surveys conducted every other year, giving us a time period of 10 years with 6 study periods. Data on annual GDP per capita from each country were gathered from the database World Development Indicators from The World Bank (The World Bank, 2018). Figure F.4 illustrates how *Political*

Trust, our dependent variable, varies between the countries. In some countries, such as El Salvador and Panama, trust in political parties is relatively stable over time, while in other countries, such as Colombia, trust in political parties has decreased substantially since 2008.

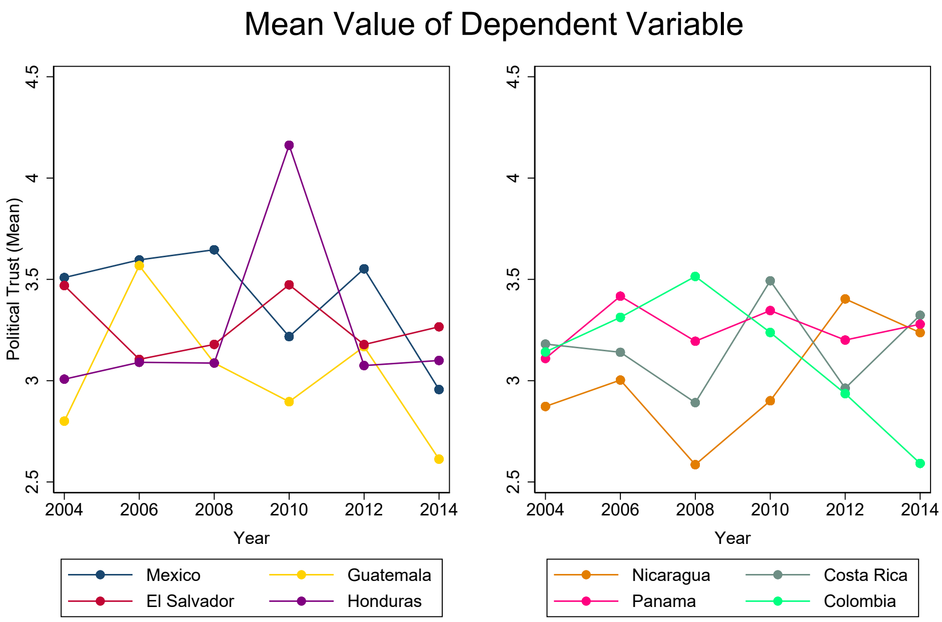

Figure F.4: Mean Value of Dependent Variable Over Time By Country (LAPOP, 2018)

3.4 LAPOP Limitations

There are certain issues one should worry about when questioning the validity of survey data in general. When investigating if the scientific standards are being met, some relevant concerns we have, among others, are related to the survey length, the sampling and to what degree the questions actually measure what they are expected to. The interviews in the AmericasBarometer lasted on average around 20 minutes, which is within the range of what is considered appropriate for the survey design to LAPOP (Mishler & Bratton, 2005). Additionally, good sampling is essential in order to get a valid inference. An ideal survey would have used random sampling, but as this is difficult to obtain in reality, another good solution is by using stratified cluster sampling (Wooldridge, 2015). LAPOP has used this approach by dividing into standard units, such as province and states, and subunits, such as city districts, in each country, and then randomly selected the sample at each level until they reached the household level. This way, the AmericasBarometer has managed to collect a sample of international standards (Mishler & Bratton, 2005).

One way LAPOP is facing the challenge of measurement error is by including several questions that measure variation of the same topic (Mishler & Bratton, 2005). The probability of capturing the opinion of a representative part of the population will therefore increase. For instance, LAPOP measures *Trust in Government*, *Trust in the National Electorate* and *Trust in Political Parties*, which is multiple measures of the similar topic. An independent evaluation of LAPOP and the democracy survey from 2005 concludes that LAPOP has "succeeded in their goal of achieving the highest standards for academic research[..]" (Mishler & Bratton, 2005).

3.5 Data Modifications

From the original LAPOP data set, our sample includes Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua, Panama, Mexico and Colombia for our analysis of the Central American area. Data were aggregated from individual level to province level for panel data analysis (different individuals for each survey). All data from LAPOP were collapsed with weights already present in the data set to account for LAPOP's cluster sampling (LAPOP, 2018b). The data set was further refined by removing provinces without observations throughout all study periods to balance the data. This gave us 132 provinces between 8 countries over 6 study periods, amounting to $N = 792$ observations.

The EM-DAT data set was created manually through information present in the EM-DAT database. Total deaths, affected, damages, magnitude, duration and natural disaster frequency on province level were extracted and merged with the LAPOP data set. Panama originally had missing observations in the variable *Province* for the year 2004. However, the variable *upm*, containing data for the primary sampling unit, corresponded uniquely with each province in a many-to-one connection. Therefore, one province had many upm-designations, but all upm-designations only had one province. This made it possible to reconstruct the data on *Province* and replace the missing observations.

Population by country in millions were extracted from the United Nations (2018), and were used to weight *Total Deaths Weighted*, *Total Affected Weighted*, and *Total Damage Weighted* from the EM-DAT data set. GDP per capita for each country were extracted from The World Bank (2018) and ln-transformed to decrease kurtosis and skewness in an attempt to get the variable closer to a normal distribution. To be able to use the EM-DAT variables in our regression, missing values were assumed to be, and replaced, with 0.

4 Empirical Strategy

The basis for the empirical analysis conducted in this thesis is a fixed effects (FE) model for political trust on natural disaster occurrences with accompanying control variables. In this section, the choice of estimation method will first be presented, followed by econometric specifications of the main regression model. Lastly, a presentation of the choice of the dependent and independent variables will be given.

4.1 Choice of Estimation Method

In panel data, there can be unobserved effects in the residual that are both constant over time (time-invariant) and not constant over time (time-variant). We suspect there to be fixed effects in the model, and therefore we expect an FE model to be the basis of this analysis. The FE model is an unobserved effects model for panel data that allows for an arbitrary correlation between the unobserved effects and the independent variables in each time period (Wooldridge, 2015). FE modelling is typically used when fixed time-invariant effects are assumed and there is no need controlling for time-invariant variables directly.

We construct a regression with a pooled OLS and a random effects (RE) model to compare it with the FE model, in order to take a better look at our assumption about the presence of fixed effects. We believe there to be both province fixed effects (time-invariant) and time fixed effects (time-variant) in the error term that affect both *Political Trust* and *Occurrence*, which is our variables of interest. Our study revolves around weather-related natural disasters, so geographical favorable/unfavorable conditions (like being close to a river, situated along the coast, or rich in forested areas) that are different from each province increase or decrease the likelihood of natural disaster events. Difference in culture and tradition (e.g. tradition for supporting a specific political party or ingrained cultural beliefs) and conditions that affect all provinces (like climate change or the financial crisis of 2008), are expected fixed effects in our region.

As we suspect fixed unobserved time-invariant province effects, a_i, to exist, both RE and FE could be applied. Pooled OLS will in this case have an omitted variable bias due to not controlling for the fixed effects. LSDV, the least squares dummy variable approach, was discarded due to clustering the standard errors over the province level, which effectively renders all t-statistics in the LSDV model invalid. This happens because the LSDV model includes dummies for all provinces, minus the base dummy, occupying all degrees of freedom in the clustered model, leaving none for parameter estimation. First difference modelling (FD) was also considered. Under the assumption of homoscedasticity and no serial correlation, FE is more efficient than FD (Wooldridge, 2015). FD also removes a substantial amount of the observations due to first differentiating, which effectively removes one time period from the data set. While we do not expect homoscedasticity nor absence of autocorrelation, clustering gives us robust standard errors that allow for their presence. This reason, and the loss of observations, leaves us with the within estimation method for fixed effects modelling, which is further explained in the next section 4.2. The choice between RE and FE rests on the independence of the individual-specific effect in the error term and the independent variables in the regression. While the RE model is more efficient than FE, it does not allow for a correlation between a_i and the independent variables. The FE model, however, allows for this.

A Hausman test will be conducted to formally test whether the FE or RE model should be used. The Hausman test checks the difference between the coefficients of the two models to see if they are significantly different. Due to the higher efficiency of RE, using the RE model is preferable if the estimates are sufficiently close. If the Hausman test is rejected, in other words, there is a systematic difference between the coefficients of the two models, FE is preferred. The reason for choosing FE in this analysis is that we assume the key assumption for the RE model, that a_i is uncorrelated with the independent variables, to be false. This would also be the argument for choosing the within estimator (FE) over the between estimator (RE). The between estimator does not consider relevant variation in the variables over time, and when a_i is correlated with the explanatory variables, the between estimator is biased. Even if FE seems to be our preferred estimation method, there are certain limitations to be aware of. One limitation to the FE model is that effects from variables with small within-variation can not be estimated. In addition, variables that do not vary over time (like country area), are omitted due to time-demeaning. Yet, time dummy variables can be included to capture effects that vary over time. Including time dummies should however be treated with caution, as more variables in a model can lead to more "noise" and overfitting, which might challenge the inference of the model. (Wooldridge, 2015)

For an FE estimator to be unbiased and consistent, there are four assumptions that need to be met (Wooldridge, 2015). The first assumption requires the FE model to be linear, while assumption two needs the sample to be random across the provinces. Both assumptions are met. The random sampling is argued for in section 3.4, and we assume no sample selection bias (apart from the disaster criteria, which makes the disaster selection not completely random) in the EM-DAT data. Our main regression model is a linear model, presented in the identification strategy in the next section. The third assumption requires the independent variables to change over time, and does not allow for perfect linearity between the independent variables. Such time constant variables could be population and province areas. After checking the correlation between the variables in our models, we find no problems with large correlation coefficients or perfect collinearity between the variables, as seen in the correlation tables A.5 through A.8 in the appendix. The most important assumption is the fourth assumption, also known as the strict exogeneity assumption. This assumption allows for a correlation between the explanatory variables and the unobserved effect, a_i, but does not allow for a correlation between the explanatory variables and the idiosyncratic error term, u_{it}. This is critical for obtaining consistent and unbiased estimates, indicating that no shared preferences across provinces should exist. Nevertheless, it could be reasonable to assume a common understanding of political performance among citizens in a country, and that political perception is not limited to be common only at the province level. To statistically test for cross-sectional independence, a Pesaran test and a Friedman test are conducted (Hoyos & Sarafidis, 2006; May & Nilsen, 2015). The tests are suited for panels with small T and high N, which is the case of our data. The null-hypothesis in both tests is that the cross-sections are independent. After conducting the tests, we get p-values from the Pesaran test (p-value = 0.1505) and the Friedman test (p-value = 1.0000), and we fail to reject the null-hypothesis. This indicates that there are no interdependence between the provinces that affects our data notably.

4.2 Identification Strategy

Fixed effects analysis will be used for a study period of T = 6 years over a time period of 10 years. The period in question is from 2004-2014 with $\Delta_t = 2$, giving us data for 2004, 2006,...,2014. The unit of analysis is province-year. The main regression model in this study is as follows:

$$\textit{Political Trust}_{it} = \beta_0 + \beta_1 \textit{Occurrence}_{it} + \beta_2 C_{it} + \gamma_i + \lambda_t + (a_i + u_{it}) \tag{1}$$

where i and t are subscripts denoting province i and year t. β_0 is the constant term. The parameter of interest is β_1, and is estimating the relationship between *Political Trust* and *Occurrence*. β_2 is the coefficient of all of the independent control variables excluding *Occurrence*, while C_{it} is the estimator for the control variables. The choice of all variables used in the main regression model will be further elaborated in section 4.3. The province fixed effects are captured in γ_i, and the variable controls for average differences between the provinces that are stable over time. By example, this could be differences in climate or topography, all relatively stable over time (relative to our time period). λ_t refers to year fixed effects, where the time dummies, λ_t, control for average differences between the years that is the same in all provinces. Such effects could be political events or economic recession that affect the whole region. The error term consists of a_i, the unobserved fixed time-invariant province effects, and u_{it}, representing all other unobserved effects across i and t.

Data on Y_{it}, $Occurrence_{it}$, C_{it}, γ_i, λ_t, a_i, and u_{it} have all been time-demeaned. This results in the exclusion of time-invariant independent variables and therefore γ_i, and the disappearance of the unobserved time-invariant effect a_i, which is what allow the model to have correlation between the independent variables and the unobserved fixed effects. OLS regression on these time-demeaned variables is called the fixed effects or the within estimator (Wooldridge, 2015). Note that this is not the case for the idiosyncratic error term, which still needs to have an expected mean value of 0, or else the condition of strict exogeneity will not hold and the estimates will be biased. Furthermore, our robust standard errors are clustered over province. There are different reasons for this. First, the individual level data were obtained using stratified cluster sampling and not by random selection, and then, as a general rule, one should cluster the standard errors (Abadie et al., 2017). Clustering also allows for the presence of heteroscedasticity and autocorrelation. While neither lead to biased estimates, underestimated standard errors and overestimated t-statistics are common (Wooldridge, 2015). Usually, it is safer to cluster at the highest level (in our case country), but having only 8 clusters will severely limit our degrees of freedom for parameter estimation (Abadie et al., 2017).

We will start the analysis by regressing weather-related natural disasters as one unit encompassed by the variable *Occurrence*. Further, we want to have a look at how different forms of *Occurrence* behave in the same regression to better be able to look at how changes in frequency might affect political trust in our region. More precisely, *Occurrence* is substituted with frequency dummies and grouped frequency dummies in the model. The frequency dummies will reflect the effect of 1, 2,...,n number of natural disasters happening in a province over a two-year period (further explained in Section 4.3.2), as opposed to no natural disasters happening in the same period. The model is based on equation (2) below. The grouped dummies will reflect low, medium and high frequency of natural disasters, as opposed to no disasters, and are shown in equation (3). Furthermore, we continue by separating the subgroups to investigate if the different types of disasters can have varied effects on political trust. Therefore, hydrological, meteorological and climatological natural disasters are analyzed separately to detect a potential difference in the results.

$$\textit{Political Trust}_{it} = \beta_0 + \delta_1 \textit{Occurrence\_ 1}_{it} + ... + \delta_6 \textit{Occurrence\_ 6}_{it} + \gamma_i + \lambda_t + (a_i + u_{it}) \quad (2)$$

$$\textit{Political Trust}_{it} = \beta_0 + \eta_1 \textit{Occurrence\_ Low}_{it} + ... + \eta_3 \textit{Occurrence\_ High}_{it} + \gamma_i + \lambda_t + (a_i + u_{it}) \quad (3)$$

4.3 Choice of Variables in the Main Regression Model

4.3.1 Dependent Variable

Political Trust is our dependent variable of interest. More specifically, this variable measures trust in political parties by province, and is collected from the AmericasBarometer. The question is phrased "To what extent do you trust the political parties?", using a 7-point response scale where 1 is "Not at all" and 7 represents "A lot", including an additional option to respond "Don't Know". This form of quantifying political trust is widely used, however, one can question how good this measurement actually is (Fisher et al., 2010). As Fisher et al. (2010) point out, this way of measuring political trust is valid when thinking of trust as one-dimensional, but not when thinking that political trust can be in different forms. Nevertheless, as mentioned earlier, dividing trust into different forms is not of much relevance empirically, thus we can rely on the validity of our dependent variable. *Political Trust* was also the "best" variable provided by LAPOP as measurement of political trust, as other measures had a significant amount of observations missing.

4.3.2 Control Variables

Prior studies have identified several potential determinants that can affect political trust (Citrin, 1974; Newton, 2001; Christensen & Lægreid, 2005; Cook & Gronke, 2005; King, 1997). Information provided by these studies is taken into considerations in our identification strategy. From LAPOP, we have used the following sociodemographic and trust variables: *Ideological Scale, Support in Political System, Trust in Local Government, Religious Attendance, Education, Age*, and *Male Ratio*. All LAPOP variables are aggregated from individual to province level, so each variable contains the weighted mean of the individuals in each province.

Ideological Scale measures where on the left-right political scale people identify themselves and is quantified with a 10-point response scale from "Not at all" to "A lot". *Support in Political System* tells to what degree citizens think one should support the political system, while *Trust in Local Government* shows the level of trust a population has in the local or municipal government, both variables with a 7-point response scale from "Not at all" to "A lot". For instance, scholars have found evidence that political awareness and left-right position are of relevance for political trust, and that citizens supporting the current political party in government have more political trust (Newton, 2001; Citrin, 1974). It is important to note that the aforementioned variables are somewhat ordinal in nature. We do, however, for the purpose of analysis (and we find it reasonable to), assume that the response scale reflects a linear spacing, i.e. the variables operate as if they were intervals.

Religious Attendance shows how often individuals attend meetings of a religious organization. This is measured on a 4-point response scale where 4 is "Never", 3 is "Once or twice a year", 2 is "Once or twice a month" and 1 is "Once a week". We use this variable as a proxy for religious conviction, however, it can be discussed how good of a proxy this actually is. People are not necessarily more religious if they often attend religious meetings. Curiosity, conscience and tradition might be just as good explanations for the frequency of meetings. Nevertheless, controlling for religious conviction agrees with current literature (Cook & Gronke, 2005), and it is the best proxy available to us through LAPOP. Nonetheless, this variable is completely ordinal, and it can not be treated as an interval. This makes statistical inference on the variable in question difficult, as the coefficient will not make much sense (UCLA, 2018). One can, however, say something about the direction of the coefficient, if religious conviction leads to increased or decreased political trust. Ultimately, we do not worry too much about this, as our independent variable of interest is *Occurrence*.

Trust in political parties might have a tendency to differ between gender, which can be justified by a worldwide survey from 2013 that found that men tend to know more about politics than women (Curran et al., 2008). Thus, *Male Ratio* is included as a control variable in our research strategy. The variable in question acts as a ratio, where the variable is expressed on a range from [0,1]. We also include the age of individuals to control for difference of political trust across age. We believe that *Age* has a form of non-linearity expressed as diminishing returns. This is because a person is less likely to change their opinions and allegiances, or that the change is of a lesser magnitude when they get older compared to younger people (Roberts, Walton, & Viechtbauer, 2006). For instance, older people are traditionally seen as more conservative than younger people. Age^2 is included to identify this specific non-linearity. *Education* contains the amount of years attended at school, and is included to control for a potential change in the perception of political trust when people get more education. One plausible assumption is that people with longer education have a deeper knowledge about the society, and are therefore more politically oriented than people with less education. Hence, one can assume that political trust differ with years of schooling.

We control for time and province effects with the variables *Year* and *Province*. From the World Bank, we have data on GDP per capita in US dollars from each country called *ln GDP*. The variable is ln-transformed in an attempt to obtain normality. While it might not be entirely correct to say the variable has a normal distribution, the ln-transformation significantly improved the skewness and kurtosis. This is our only independent variable that is at country and not province level, that is, all provinces in the same country have the same GDP per capita at time T. We are aware that this will only control for effects between provinces in different countries. However, GDP-specific data on the provinces, or other variables that could substitute for GDP are, to the best of our knowledge, not available to us.

EM-DAT provides data on natural disasters, and the variables are *Occurrence, Total Deaths Weighted, Total Affected Weighted, Total Damage Weighted, Magnitude* and *Duration*. *Occurrence* is a measure of disaster frequency for each province in a two-year period, meaning that data for 2004 incorporates natural disasters for both 2003 and 2004. The variable *Total Deaths Weighted* is the sum of dead and missing for each disaster case, and is weighted with the country population in millions. *Total Affected Weighted* is the number of total injured, homeless and affected after a disaster, and is also weighted by country population in millions. *Total Damage Weighted* is the economic consequence measured in 1000 US dollars and weighted similarly to *Total Deaths Weighted* and *Total Affected Weighted*. Data on magnitude were difficult to group without differentiating between the subgroups, as the variable does not make sense when grouping natural disasters due to different measurements (e.g. km^2 and kph). We control for the magnitude when using separate models for hydrological, meteorological and climatological disasters, but do not use *Magnitude* in our main model. The variable *Duration* contains the length of days of each natural disaster. $Duration^2$ is included to control for expected non-linearity in the form of diminishing returns (e.g. we expect a significant difference in effect between days 5 to 10 and 105 to 110).

5 Empirical Analysis & Findings

The aim of this study is to first investigate if political trust is affected by weather-related natural disasters in the long run, and second, if natural disaster frequency matters for political trust. By presenting the empirical results for the two hypothesis, H_1 and H_2, this section will give an overview of the general findings of this thesis. The analysis will first be performed by grouping the natural disasters as one unit in the regression model, then by implementing different forms of the variable *Occurrence*. We continue by adjusting the model to the different subgroups with the same analysis applied.

5.1 Model Comparison

As discussed under the empirical strategy in section 4, we have chosen to employ an FE model instead of pooled OLS and RE. All three models were created with the same specifications: identical independent variables, fixed year effects with 2004 as the base year, and standard errors clustered over province. The resulting models are shown in Table T.2. We see that the adjusted goodness of fit for the pooled OLS and FE model, as well as the overall goodness of fit for the RE model, are all between the 30-35% range. Included, but not shown, are year fixed effects. A joint significance test on the biennial dummies for all models yield strong rejection of the null hypothesis that all coefficients are statistically equal to 0, against the alternative hypothesis that at least one coefficient is statistically different from 0 (Wooldridge, 2015).

Due to having panel data on different provinces, we expect there to be fixed effects between provinces in the error term that are time-invariant and correlated with our dependent variable. If there are such effects, pooled OLS will not be unbiased because of the expected mean of the error term will no longer be 0. When regressing the FE model (unclustered), STATA runs an F-test with the null hypothesis that all $a_i = 0$. With a p-value = 0.0082, we strongly reject that the fixed effects part of the error term is statistically equal to 0, giving us an indication that pooled OLS might be biased. By looking at the coefficients in Table T.2, it reinforces our assumption regarding fixed effects due to their difference. We also see that the pooled OLS and RE model have very similar coefficients and significance level on their variables.

Table T.2: Model Comparison

	(1) Pooled OLS Political Trust	(2) Random Effects Political Trust	(3) Fixed Effects Political Trust
Occurrence	-0.01155	-0.01114	-0.00458
	(0.01261)	(0.01283)	(0.01701)
Total Deaths Weighted	0.00621***	0.00629***	0.00690***
	(0.00128)	(0.00127)	(0.00128)
Total Affected Weighted	-0.00000	-0.00000	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
Total Damage Weighted	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
Duration	0.00047**	0.00051**	0.00091***
	(0.00024)	(0.00023)	(0.00030)
Duration^2	-0.00000	-0.00000	-0.00000*
	(0.00000)	(0.00000)	(0.00000)
Education	-0.01284	-0.01222	-0.00030
	(0.01210)	(0.01206)	(0.01799)
Age	-0.12373*	-0.12183*	-0.08365
	(0.07337)	(0.07299)	(0.08268)
Age^2	0.00172*	0.00170*	0.00130
	(0.00089)	(0.00088)	(0.00100)
Male Ratio	-0.48035	-0.53947	-1.24162
	(0.58204)	(0.58982)	(0.78423)
ln GDP	0.08873**	0.08713**	0.31744*
	(0.03676)	(0.03702)	(0.17468)
Ideological Scale	0.01905	0.01476	-0.02446
	(0.02513)	(0.02535)	(0.03073)
Support in Political System	0.18471***	0.19008***	0.23955***
	(0.04037)	(0.04032)	(0.04324)
Trust in Local Government	0.32697***	0.32533***	0.31004***
	(0.03544)	(0.03566)	(0.04413)
Religious Attendance	0.11513***	0.11304***	0.09279*
	(0.04349)	(0.04355)	(0.05162)
Fixed Effects			√
Random Effects		√	
Clustered SE over Province	√	√	√
R^2 Adjusted	0.333		0.316
R^2 Overall		0.350	
Observations	792	792	792

*Notes: Table T.2 compares different estimators of our main regression model. Column (1) applies pooled OLS, while RE are used in column (2). Column (3) applies FE estimation. R^2 Overall is the R^2 for the RE, and is a weight of the within and between R^2. The independent variable of interest, Occurrence, is insignificant. Standard errors are in parentheses, with significance level denoted * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*

To further test which model should be preferred, we perform a Hausman test between the FE and RE models. The Hausman test gives a p-value = 0.006, and we reject the null hypothesis that there is no systematic difference in the coefficients between the two models. Additionally, the RE model reports $sigma_u = 0.0676$, another indication that there are fixed effects present. Based on the tests performed, the similar coefficients between pooled OLS and RE, as well as the intuition behind choice of model, further analysis will be done with the FE model. Note that the coefficient of the independent variable of interest, *Occurrence*, is not statistically significant even at the 10% level for any of the proposed models.

5.2 Empirical Results: Hypothesis 1

H_1: Weather-related natural disasters have little effect on political trust in the long run.

The results from the main FE model are displayed in Table T.3, where the final main regression model is reported in column (3). The adjusted R^2 indicates that 31.6% of the variance in the dependent variable *Political Trust* is predictable with the independent variables. The Bayesian Information Criterion (BIC) is a likelihood ratio used for model selection. BIC tries to impact a penalty for each added variable to avoid overfitting (Schwarz, 1978). A relatively smaller BIC value indicates the better model. Table T.3 suggests that the main regression model in column (3) is the best model relatively speaking, as this has the smallest corresponding BIC compared to the models (1) and (2). Model (1) displays *Occurrence* regressed on *Political Trust*, with a statistical significance at the 1% level. When we control for *Total Damage Weighted, Total Affected Weighted, Total Deaths Weighted* and *Duration* in model (2), *Occurrence* is no longer significant at any reported level and the coefficient has dropped from 0.05382 to 0.02324 with a slight increase in the standard errors. Model (3) shows the complete FE model where the rest of the independent variables have been added.

In addition, time fixed effects are controlled for through dummies, and standard errors have been clustered over province in model (3), with no indication of any evidence on political trust being affected by natural disaster events. This is in line with our first hypothesis, that weather-related natural disasters in general have little effect on political trust. Notably, the coefficient of *Occurrence* is very small, and we believe there might be a couple of reasons for this. The real value of the coefficient might be in this range, but even if the effect on political trust is statistically insignificant, we do not believe the coefficient to be this small. *Occurrence* is a frequency variable, and different frequencies might cancel each other out when combined in the same variable. Alternatively, it might be that either case is present, that there are both small real values and significant differences between the frequencies. This will be further looked at when analyzing our second hypothesis.

It is important to note that while the standard errors were slightly reduced from model (2) to model (3), the coefficient sign of *Occurrence* has changed from positive to negative. We believe there to be two main reasons for why this can happen in our case; collinearity and omitted variable bias. Sign change due to collinearity happens when two or more variables have a high correlation coefficient (Wooldridge, 2015). Table A.5 in the appendix shows the correlation coefficients between *Occurrence* and the independent variables in model (3). There are no strong correlations shown (highest at 0.331), so we dismiss collinearity as an issue. In model (2), there might be a case of an omitted variable that causes bias in such a way that *Occurrence* has the wrong sign (we expect it to be negative). By including the omitted variable in the regression, the sign will then be corrected. This typically happens when the omitted variable has a positive coefficient in the regression, but a negative correlation between the variable of interest, in this case *Occurrence* (Kennedy, 2002). If we look at *Religious Attendance* in model (3) and the correlation coefficient in Table A.5, we see that the variable fits the description. By removing the variable *Religious Attendance*, we get *Occurrence* to revert back to a positive sign, giving a strong indication that model (2) had an omitted variable bias and model (3) corrected for this. The BIC values also agree with this assessment.

We continue to analyze the regression output by focusing on the significant control variables in model (3). All analysis on the coefficients are done ceteris paribus. The results show that deaths following natural disasters have a positive effect on political trust. If 100 people die, political trust will increase with 0.690 on average. *Total Deaths Weighted* is statistical significant at the 1% level. These findings indicate that a natural disaster has to be relatively fatal for political trust to be affected. Plausible explanations for this can be that politicians think and act more readily when severe disasters strike, while smaller disasters might, on the contrary, be of less importance (do not have the same political gravitas). The perception of political performance, and thus trust, will increase as the politicians take the disasters more serious. Another way of interpreting this coefficient, is by thinking of large natural disasters as more unifying, leading to an increase in trust.

Total Affected Weighted and *Total Damage Weighted* are statistical significant at a 1% level, where 100 000 affected will reduce political trust with 0.1533 points on average, and damages worth 100 000 000 US dollars will reduce it with 0.2006 points. It is difficult to say anything about the relative magnitudes of these variables. One of the reasons for this is EM-DAT's lacking observations for economic damages. Another one is that "affected" is a broad term. It incorporates injured, homeless and otherwise affected, making inference difficult. That being said, the model shows that economical damages reduce political trust, which makes sense considering that economic damages are negative consequence following a disaster. *Total Affected Weighted* is peculiar, as one would expect it to behave like *Total Deaths Weighted*. However, considering it is the sum of different variables with a substantial amount of observations missing, bias through measurement error is possible.

The results further indicate that the duration of disasters increases political trust. The variable is statistically significant at a 1% level. The square of this variable is significant at a 10% level with a negative sign, suggesting that *Duration* might have a non-linear trend. The coefficient is quite small however (a reduction of ~0.05 after 100 days), so the diminishing returns seems to only apply for natural disasters that can have an extended duration (e.g. drought). The original variable has a coefficient that increases political trust with 0.0911 per 100 days, but with a mean value of ~77 days, the effect from duration is minimal in most cases. When it comes to GDP, the ln-transformed GDP variable is statistically significant at the 10% level. The coefficient indicates that if GDP per capita increases with 1%, political trust will increase with 0,00317 points. *ln GDP* was included to correct for economic differences.

Further findings indicate that a higher degree of believing in support in the political system, and more trust in the local government, have a positive effect on political trust. Both variables are statistically significant at the 1% level. These findings seem reasonable, that is, political trust at the local level has the same trend as the national level, and trust in political parties is more likely if you already believe in supporting the political system. For the matter of religion, religious people seem to have a negative effect on political trust compared to less religious people. As stated earlier, *Religious Attendance* is used as a proxy for how religious a person is, and is statistically significant only at the 10% level. Note that a person is less religious the higher score, as further described in Table A.4 in the appendix. From the regression output, only the year 2014 is statistically significant when compared to the base year 2004. However, due to strong indications of joint significance as mentioned earlier, we choose to include all year dummies to control for year fixed effects (Wooldridge, 2015).

Table T.3: Main Fixed Effects Model

	(1) Political Trust	(2) Political Trust	(3) Political Trust
Occurrence	0.05382***	0.02324	-0.00458
	(0.01706)	(0.01896)	(0.01701)
Total Deaths Weighted		0.00680***	0.00690***
		(0.00161)	(0.00128)
Total Affected Weighted		-0.00000	-0.00000***
		(0.00000)	(0.00000)
Total Damage Weighted		-0.00000	-0.00000***
		(0.00000)	(0.00000)
Duration		0.00120***	0.00091***
		(0.00039)	(0.00030)
Duration^2		-0.00000***	-0.00000*
		(0.00000)	(0.00000)
Education			-0.00030
			(0.01799)
Age			-0.08365
			(0.08268)
Age^2			0.00130
			(0.00100)
Male Ratio			-1.24162
			(0.78423)
ln GDP			0.31744*
			(0.17468)
Ideological Scale			-0.02446
			(0.03073)
Support in Political System			0.23955***
			(0.04324)
Trust in Local Government			0.31004***
			(0.04413)
Religious Attendance			0.09279*
			(0.05162)
Year Fixed Effects			√
Province Fixed Effects	√	√	√
Clustered SE over Province			√
R^2 Adjusted	-0.182	-0.143	0.316
BIC	1039.7	1040.1	850.1
Provinces	132	132	132
Observations	792	792	792

*Notes: The main FE model is reported in this table. Column (3) is the final model, and columns (1) and (2) are step-wise adding additional variables to the model to evaluate the variables. Column (2) includes only disaster-specific variables, while year dummies, sociodemographic and socioeconomic variables are added in column (3), along with clustered standard errors. BIC measures the likelihood of a model to be relatively best while controlling for overfitting. Column (3) has the smallest BIC, indicating that this model is a better fit than the other models. Standard errors are in parentheses, with significance level denoted * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

5.3 Empirical Results: Hypothesis 2

H_2: Higher frequency of weather-related natural disasters has a negative impact on political trust.

The frequency of natural disasters is incorporated in our regression model in multiple ways, and the results from columns (1-3) in Table T.4 will now be examined. In general, there is little variation between the coefficients of the control variables in the three columns, thus they will not be further examined as they are already analyzed in section 5.2. Insignificant coefficients with exception of the frequency variables, are not reported in the table.

The main FE model, also presented in Table T.3, is reported in column (1) in Table T.4. As earlier stated, this variable is not statistically significant, an indication that natural disaster frequency does not influence political trust. The total number of natural disaster occurrences a province has experienced during a single two year study period is 6 disasters. Therefore, column (2) splits the frequency variable into 6 dummies, with frequency range [0,6], where no natural disasters occurring is the base of analysis. We see from the regression table that a frequency of 2 has a positive coefficient, which is significant at the 10% level, telling us that political trust increases with ~0.11 points should a province experience 2 natural disasters as opposed to none. The other significant dummy in the model is frequency of 6, which is significant at the 1% level. The coefficient has a negative sign this time, indicating that political trust decreases with ~0.34 points should a province experience 6 natural disasters as opposed to none. There are, however, only 5 instances of *Occurrence = 6*, which weakens the inference substantially due to lack of observations (Wooldridge, 2015).

The last regression model in column (3) has categorized natural disaster frequency into different groups; *Occurrence Low* (1-2 occurrences), *Occurrence Medium* (3-4 occurrences), and *Occurrence High* (5-6 occurrences). The omitted base value is *Occurrence None*. From the model, we see that only *Occurrence Low* is significant at the 10% level, while *Occurrence Medium* and *Occurrence High* are statistically insignificant. However, the coefficients have a clear trend for both models in columns (2) and (3), illustrated with a plot for the dummy coefficients in Figure F.5. A negative exponential correlation between natural disaster frequency and political trust can be seen, though the margins for some of the coefficients are relatively large.

Table T.4: Natural Disaster Frequency Models

	(1) Political Trust	(2) Political Trust	(3) Political Trust
Occurrence	-0.00458		
	(0.01701)		
Occurrence = 1		0.09108	
		(0.05716)	
Occurrence = 2		0.10942*	
		(0.05946)	
Occurrence = 3		0.02962	
		(0.07328)	
Occurrence = 4		0.00115	
		(0.07486)	
Occurrence = 5		-0.09603	
		(0.15729)	
Occurrence = 6		-0.33820***	
		(0.11665)	
Occurrence Low			0.09859*
			(0.05271)
Occurrence Medium			0.01975
			(0.06570)
Occurrence High			-0.15526
			(0.13429)
Total Deaths Weighted	0.00690***	0.00732***	0.00749***
	(0.00128)	(0.00128)	(0.00126)
Total Affected Weighted	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
Total Damage Weighted	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
Duration	0.00091***	0.00082**	0.00085***
	(0.00030)	(0.00032)	(0.00031)
Duration^2	-0.00000*	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)
ln GDP	0.31744*	0.31479*	0.31979*
	(0.17468)	(0.17351)	(0.17107)
Support in Political System	0.23955***	0.23731***	0.23871***
	(0.04324)	(0.04385)	(0.04326)
Trust in Local Government	0.31004***	0.31482***	0.31416***
	(0.04413)	(0.04453)	(0.04396)
Religious Attendance	0.09279*	0.08813*	0.08937*
	(0.05162)	(0.05095)	(0.05041)
Year Fixed Effects	√	√	√
Province Fixed Effects	√	√	√
Clustered SE over Province	√	√	√
R^2 Adjusted	0.316	0.323	0.325
Provinces	132	132	132
Observations	792	792	792

Notes: This table includes models where Occurrence is implemented in different ways. Column (1) is our main regression model with one variable for Occurrence, while column (2) has split the frequency variable into 6 dummies, with frequency range [0,6]. The omitted variable is Occurrence = 0. The dummies are grouped in column (3), categorized as Occurrence Low (1-2 occurrences), Occurrence Medium (3-4 occurrences) and Occurrence High (5-6 occurrences), with Occurrence None as omitted variable. Standard errors are in parentheses, with significance level * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

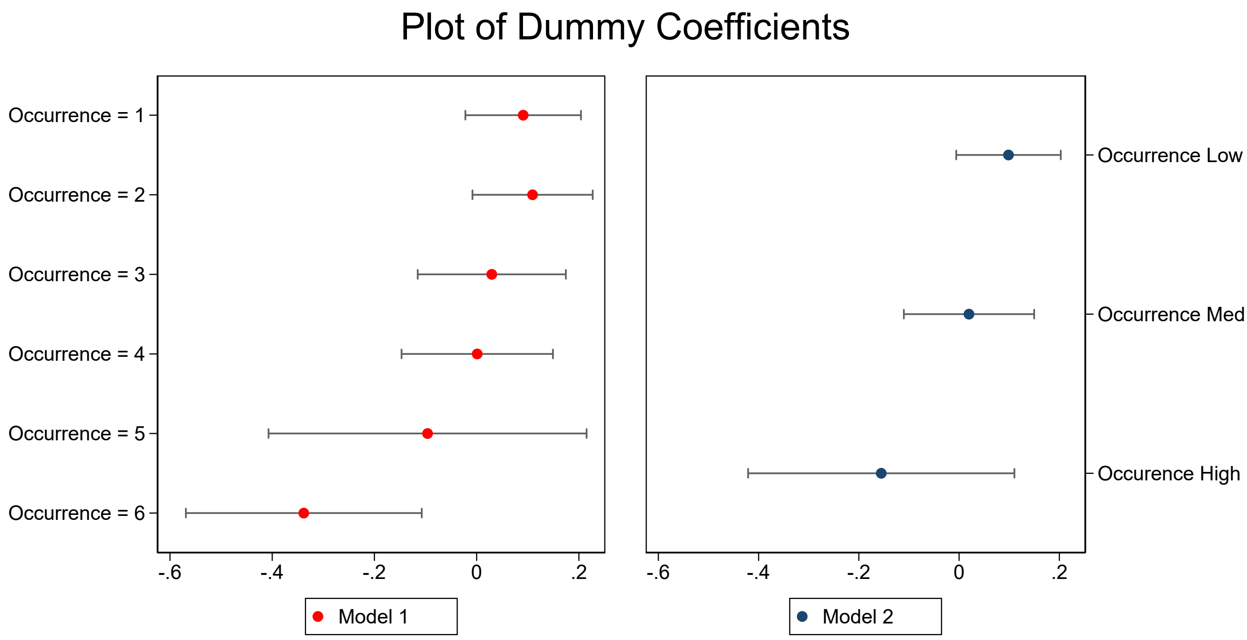

Figure F.5 shows the coefficients of the dummy variables for Occurrence in models (2) and (3) in Table T.4. The x-axis represents the value of the coefficients for the dummies. Base value for the dummies are 'Occurrence = 0' and 'Occurrence None'.

Figure F.5: Plot of the Occurrence Dummy Coefficients

5.4 Empirical Results: Subgroups

We have divided the regressions in Table T.5 into the different subgroups of weather-related natural disasters, which corresponds to hydrological, meteorological, and climatological natural disasters. Similar to Table T.4, the models are estimated with different forms of our frequency variable. Note that because the data are differentiated between subgroups, the table does not include grouped dummies due to lack of observations at the same frequencies. Columns (1), (3), and (5) are the main regression models for each subgroup with the variable *Occurrence* split into *Hydrological*, *Meteorological* and *Climatological*. Columns (2), (4), and (6) include frequency dummies. Descriptive statistics of the variables in the differentiated models can be found in Table A.3 in the appendix. Joint significance tests have been performed on year fixed effects in the subgroup models as well, and all null hypotheses of no joint significance were strongly rejected. A variable for magnitude has been included as a new addition in all columns. The variable is measured in square kilometers for hydrological and climatological disasters, and kilometers per hour for meteorological disasters. Even so, magnitude does not show any statistical significance. The other independent variables do not have any significant changes in coefficient signs or size, and are left out of the table.

The coefficients of the frequency variable and frequency dummies in models (1) and (2) for hydrological disasters are not statistically significant, nor are the variable significant in model (3) for meteorological disasters. However, model (4), containing the dummies for meteorological disasters, have numeral significant coefficients. $M = 1$ is statistically significant at the 10% level, increasing political trust with ∼0.115 points if a single meteorological disaster occurs as opposed to none. This is consistent with the main model. Furthermore, when the frequency increases to 4 or 6, statistical significance increases to the 1% level and we get a negative effect. There are a ∼0.59 point reduction in political trust with a disaster frequency of 4, and a ∼0.74 point reduction with a frequency of 6, as opposed to no disasters. This is also consistent with the main model, admittedly with greater coefficient size.

In the analysis of H_1, the reason for the low coefficient of *Occurrence* was discussed, and one of the arguments presented was significant difference between the dummy coefficients. An F-test was performed on the frequency dummies in models (2), (4), and (6) with null hypothesis of equal coefficients and alternative hypothesis that at least one coefficient is different. The test on model (2) returned a p-value of 0.1377, model (4) a p-value of 0.0001, and model (6) a p-value of 0.0415. While we can not reject the null hypothesis for model (2), we can reject it on a 1% level for model (4) and a 5% level for model (6). Since the coefficients have different signs as well, this could be the reason for the (in our opinion) low coefficient of *Occurrence* in the main model. It might be that the flipping of signs on the coefficients happens because low frequencies can be easier for the politicians to manage, and therefore the perception of political performance can increase. On the other side, multiple disasters happening over a relative short span of time can be challenging for the politicians as it presents a more complex situation, and one could imagine there to be more room for improvement regarding political disaster management with higher disaster frequencies.

Inference should be done with caution in these models as well, with only 3 instances of $M = 4$ and 1 instance of $M = 6$. Climatological disasters only have observations at frequencies of 0, 1, and 2, making it difficult to say anything about higher frequencies regarding this subgroup. Model (5) tells us that climatological disasters increase political trust with ∼0.17 points for every occurrence. Considering the observations just mentioned, it seems consistent with the main model only with a greater coefficient size. Model (6) consists of dummies for frequencies of 1 and 2, where the second dummy is statistically significant at the 5% level, increasing political trust with ∼0.50 points when there are 2 occurrences instead of none. Be aware that the number of instances where the frequency equals 2 is only 6.

Table T.5: Subgroup Models

	(1) Political Trust	(2) Political Trust	(3) Political Trust	(4) Political Trust	(5) Political Trust	(6) Political Trust
Hydrological	-0.01684					
	(0.02942)					
H = 1		0.07362				
		(0.04547)				
H = 2		-0.01863				
		(0.07722)				
H = 3		-0.16431				
		(0.11021)				
H = 4		-0.01581				
		(0.14088)				
H = 5		-0.12497				
		(0.14034)				
Meteorological			-0.00919			
			(0.04817)			
M = 1				0.11472*		
				(0.05929)		
M = 2				-0.01963		
				(0.12036)		
M = 3				-0.21195		
				(0.16225)		
M = 4				-0.58713***		
				(0.22287)		
M = 6				-0.74181***		
				(0.19995)		
Climatological					0.16941**	
					(0.08458)	
C = 1						0.13740
						(0.09571)
C = 2						0.50480**
						(0.19763)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
Province Fixed Effects	✓	✓	✓	✓	✓	✓
Clustered SE over Province	✓	✓	✓	✓	✓	✓
R^2 Adjusted	0.298	0.304	0.298	0.309	0.305	0.305
Provinces	132	132	132	132	132	132
Observations	792	792	792	792	792	792

Notes: Fixed effects are applied in all models. The frequency of natural disasters is incorporated in our regression model in two different ways for each subgroup. Columns (1), (3), and (5) are the main regression models for each subgroup with one variable for Occurrence. Columns (2), (4), and (6) split the frequency variable into dummies depending on the total number of natural disaster events one province in a country has experienced. This corresponds to a a range from [0,5] for hydrological disasters, [0,6] (no value for #5) for meteorological, and only [0,2] for climatological disasters. The climatological variable has very few observations, and should be treated with extra caution. Standard errors are clustered over province and reported in parentheses, with significance level denoted * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

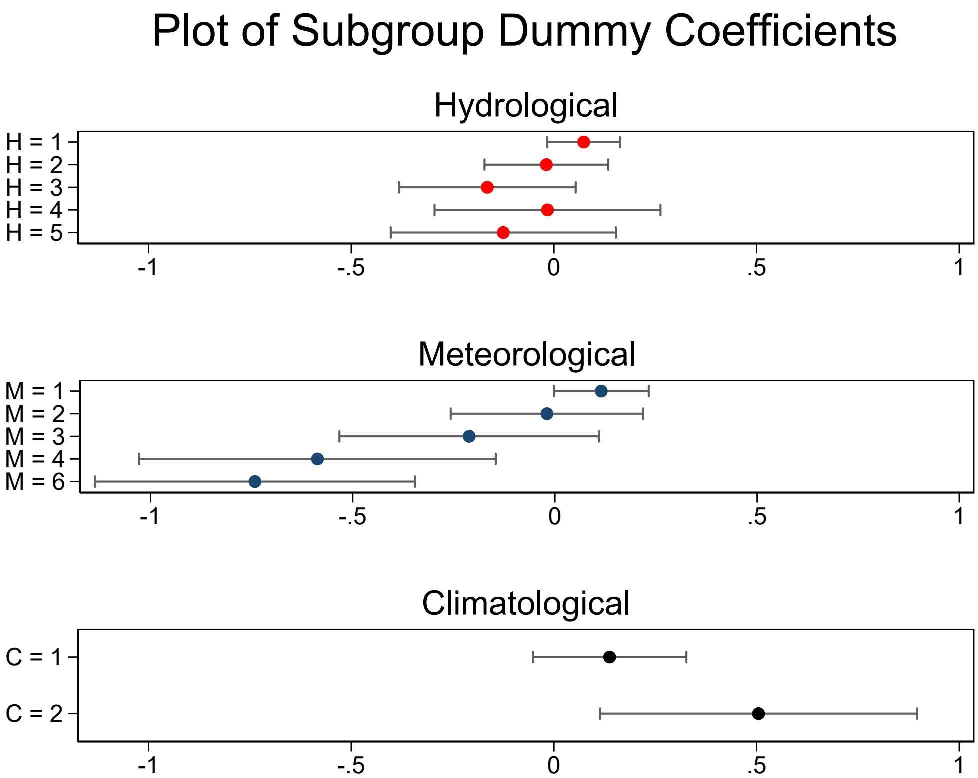

Figure F.6 shows the coefficients of the dummies in models (2), (4) and (6) in Table T.5. The y-axis represents the coefficient value of the dummies. Base value for the dummies are H = 0, M = 0 and C = 0 respectively.

Figure F.6: Plot of the Occurrence Dummy Coefficients of Subgroups

5.5 Summary of Findings

H_1: *Weather-related natural disasters have little effect on political trust in the long run.*

This is the first of two hypotheses in our paper, and based on the findings in the analysis, it seems to hold. The results are in line with current literature on the subject (Albrecht, 2017a). For the main model, *Occurrence* is insignificant at all levels with a very small coefficient (-0.00458) that, even if it were statistically significant, would not affect political trust to any substantial degree. The differentiated models tell the same story, except for model (5) in Table T.5. However, the model suffers from no observations of higher frequencies, which makes inference without assuming the model only holds for low frequencies difficult.

H_2: *Higher frequency of weather-related natural disasters has a negative impact on political trust.*

For the second hypotheses, there are some weak signs of a negative effect on political trust at a relative high level of natural disaster frequency, but not enough to draw any conclusions. It is uncertain whether the statistical significance in model (3) in Table T.4 or models (4) and (6) in Table T.5 are due to an actual effect on political trust, or by faulty correlation through lack of observations. There are however a stronger indication that a low frequency of natural disasters has a mild effect on political trust. *Occurrence = 2* in model (2) and *Occurrence Low* in model (3) in Table T.4, and *M = 1* in model (4) and *Climatological* in model (5) in Table T.5 all point toward affecting political trust positively. This is also reflected in the coefficient plots of the dummies, which show that low frequencies have positive coefficients that decrease with an increase in natural disaster frequency. The exception is the plot for climatological disasters, but lack of higher frequencies, as said before, makes it difficult to trust in the interpretation.

6 Robustness Checks

This section discusses different robustness checks that are relevant to this study. We identify autocorrelation and heteroskedasticity, overfitting, and listwise deletion of provinces in the data set, as potential factors that may challenge the validity of this analysis. Lastly, we perform a robustness check by changing our dependent variable, *Political Trust*, to see how the model responds.

The presence of heteroskedasticity and autocorrelation can, as stated earlier, cause underestimated standard errors and overestimated t-statistics. Therefore, we perform a Wooldridge test for autocorrelation in panel data with a linear model (Wooldridge, 2002). According to Drukker (2003), the test results have good size and power properties in reasonable sample sizes (large N, small T). The test operates under the null hypothesis of no first-order autocorrelation. Performing the test on our dependent and independent variables (excluding the year dummies) gives us a p-value of 0.992. We fail to reject the null hypothesis at any reasonable level, which gives a strong indication that autocorrelation is present. To check for presence of heteroscedasticity, we plot the residuals against the fitted values. The resulting scatter plot is shown in Figure F.7. As one can see, there is a clear pattern of no homoscedasticity in our data. We solve these problems by allowing their presence through clustering our standard errors.

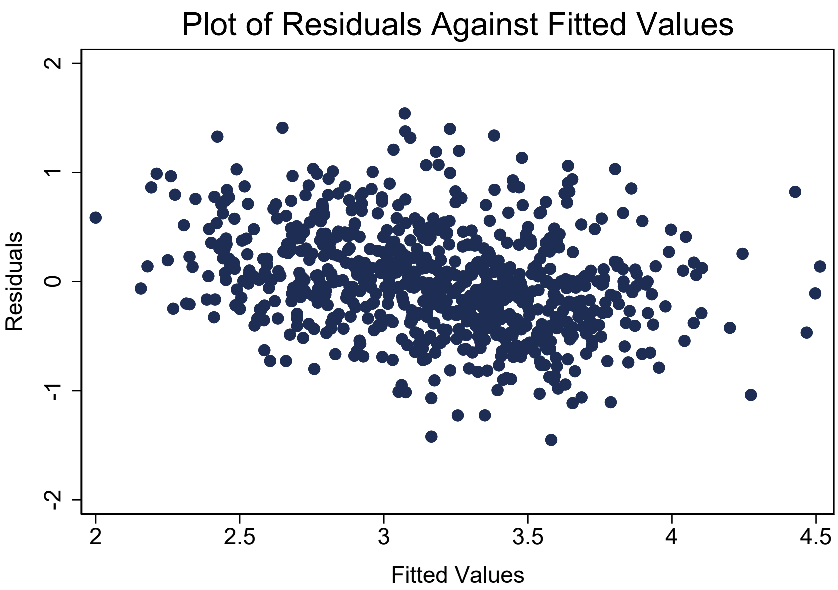

Figure F.7: Heteroscedasticity Plot

Overfitting occurs when too many independent variables are fitted to a regression model. The model will then estimate sampling variances that are needlessly large, which gives the estimators relative poor precision (Burnham & Anderson, 2002). This also tends to lead to spurious regression by including spurious variables. Spurious variables are variables that show statistical significance when there are none (Wooldridge, 2015). As such, one should balance overfitting and underfitting to get a parsimonious (the best possible) model. We are primarily concerned about overfitting in our model, especially due to the inclusion of dummy variables of *Occurrence*, and since both dead, affected and damages are included from the EM-DAT data in the regression model. This is highlighted by the sign of the coefficient of *Total Deaths Weighted*, where the positive effect on political trust were slightly unexpected. This might, however, come from endogeneity problems through measurement errors in the EM-DAT data, which might be the greatest uncertainty related to our analysis. We are not too concerned about *Occurrence*, but the available data on *Total Deaths Weighted, Total Affected Weighted, Total Damage Weighted*, and the magnitude variables in the split models, are not ideal. This is especially the case for *Total Damage Weighted* and the magnitude variables, where only 233 out of 585 natural disasters have reported any incurred economical damage at all, and even those numbers, as stated in the EM-DAT limitations, have been underestimated. Furthermore, no climatological disasters have any reported magnitude numbers, and they are severely lacking in regards to hydrological and meteorological disasters as well. Over/underfitting is difficult to formally test for, and we need to rely on economic intuition to decide whether this is a problem in the model. In our case, we have a number of variables that are statistically insignificant, but they are supported by current literature, as well as our own arguments for including them. Removing variables that should be included, even if they are statistically insignificant, also leads to bias (Wooldridge, 2015).

To balance our panel data, we performed listwise deletion of provinces that did not have observations for every study period. This results in the total amount of observations being reduced 858 to 792. While the amount (~7.7% decrease) of observations lost is relatively small, there is always a case to be made for bias in instances like this. This is unless one can be sure that the reason for the missing data is completely random, though that is seldom the case. We can not find any information through LAPOP or anywhere else why some provinces miss data for certain years. To check if there might be any substantial bias due to dropping observations, we perform a regression with the same model on both the balanced and unbalanced data. We exclude showing insignificant control variables. The results are listed in Table T.6 below. There is no substantial change in either standard errors nor coefficients between the two models. Considering this, we assume that any potential bias coming from listwise deletion does not affect our data to any significant degree.

Table T.6: Balanced Data and Unbalanced Data

	(1) Political Trust	(2) Political Trust
Occurrence	-0.01229	-0.00458
	(0.01715)	(0.01701)
Total Deaths Weighted	0.00681***	0.00690***
	(0.00126)	(0.00128)
Total Affected Weighted	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Total Damage Weighted	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Duration	0.00088***	0.00091***
	(0.00029)	(0.00030)
Duration^2	-0.00000*	-0.00000*
	(0.00000)	(0.00000)
ln GDP	0.28444*	0.31744*
	(0.16929)	(0.17468)
Support in Political System	0.24065***	0.23955***
	(0.04132)	(0.04324)
Trust in Local Government	0.31451***	0.31004***
	(0.04078)	(0.04413)
Religious Attendance	0.11176**	0.09279*
	(0.04804)	(0.05162)
Year Fixed Effects	√	√
Province Fixed Effects	√	√
Clustered SE over Province	√	√
R^2 Adjusted	0.329	0.316
Provinces	140-146	132
Observations	858	792

*Notes: This table presents the same regression model on unbalanced data, column (1), and balanced data, column (2). There is no substantial change in either standard errors nor coefficients between the two models. The significance level is denoted * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, with standard errors in parentheses.*

We would also like to perform a check for robustness through changing our dependent variable. Similar variables with the same amount of observations are, unfortunately, a rare commodity in our data set (in our region). The best option available to us is *Trust in the Justice System*, which is a variable where the respondents were asked how much they trust the justice system in their country, using the same scale as *Political Trust*. On paper, they are both trust variables with the same scale, and since political parties (our political trust variable), the ones in power at least, dictate the laws surrounding judicial processes, we expect there to be a significant correlation between the variables. A scatter plot between the two variables with a fitted line and the corresponding correlation coefficient is shown in Figure F.8. As we can see, there is considerable correlation both visually and as signified by a correlation coefficient of 0.6035.

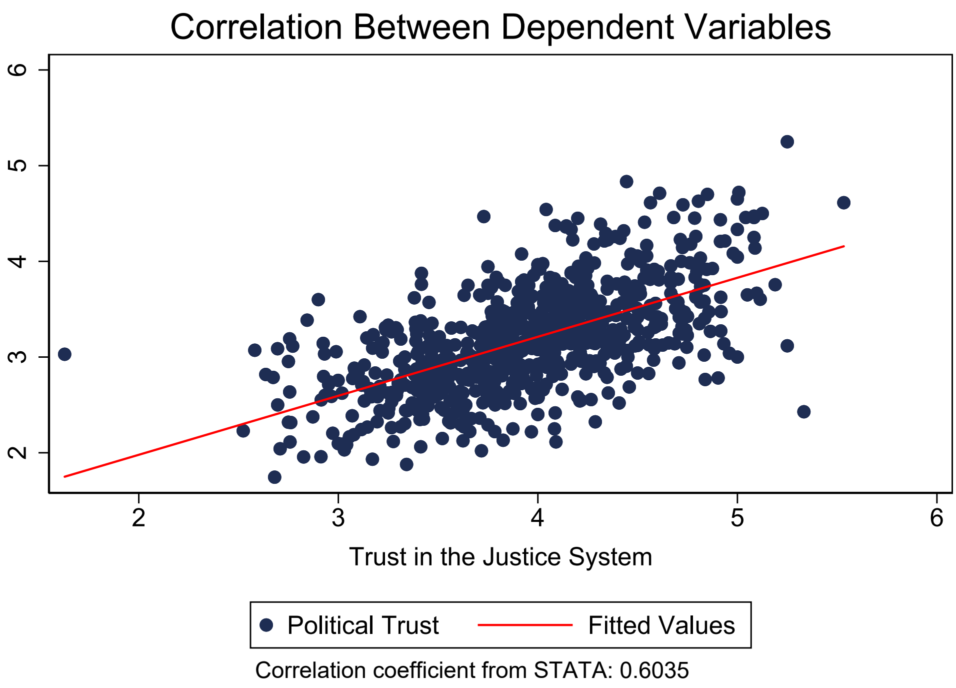

Figure F.8: Scatterplot Political Trust and Trust in the Justice System

Table T.7 reports the regression outputs when two different dependent variables are used, *Political Trust* and *Trust in the Justice System* respectively. The model from column (2), with *Trust in the Justice System* as dependent variable, has smaller standard errors and a substantial higher adjusted R^2 compared to the main model in column (1). Interestingly, the coefficients of *Occurrence* show different signs in the two columns, though neither are statistically significant. Even though some coefficients act differently in the two models, many of the same trends are consistent. *Total Affected Weighted*, *Total Damage Weighted*, *ln GDP*, *Support in Political System* and *Trust in Local Government* are significant with the same coefficient signs. We see that *Duration* and its squared form have lost significance, which makes sense due to the difference between the dependent variables. *Total Affected Weighted* and *Religious Attendance* have also lost significance and changed sign, while *Education* are now significant at the 5% level. Due to the relative difference of the new dependent variable, changes in the coefficients to this degree were not unexpected. It does, on the other hand, make saying anything about the robustness of the model through dependent variable substitution, difficult. It is hard to say if the changes come from specification faults or simply the lack of a better proxy in the alternative model. Still, we think there are enough variables that behave the way we expect them to, and conclude that the specification holds.

Table T.7: Different Dependent Variables

	(1) Political Trust	(2) Trust in the Justice System
Occurrence	-0.00458	0.01327
	(0.01701)	(0.01377)
Total Deaths Weighted	0.00690***	0.00185**
	(0.00128)	(0.00079)
Total Affected Weighted	-0.00000***	0.00000
	(0.00000)	(0.00000)
Total Damage Weighted	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Duration	0.00091***	0.00039
	(0.00030)	(0.00028)
Duration^2	-0.00000*	0.00000
	(0.00000)	(0.00000)
Education	-0.00030	-0.03199**
	(0.01799)	(0.01554)
ln GDP	0.31744*	0.53819***
	(0.17468)	(0.13065)
Support in Political System	0.23955***	0.47955***
	(0.04324)	(0.03020)
Trust in Local Government	0.31004***	0.26263***
	(0.04413)	(0.03698)
Religious Attendance	0.09279*	-0.01880
	(0.05162)	(0.04495)
Year Fixed Effects	√	√
Province Fixed Effects	√	√
Clustered SE over Province	√	√
R^2 Adjusted	0.316	0.549
Provinces	132	132
Observations	792	792

*Notes: Column (1) reports the output from the main FE regression model with the dependent variable Political Trust. The model in column (2) is the same, with exception of the dependent variable, Trust in the Justice System. The significance level is denoted * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, with standard errors in parentheses.*

7 Discussion

7.1 Discussion of Findings

This study contributes to a better understanding of natural disasters and their consequences, which is relevant as the forecast for weather-related natural disasters shows an increase in frequency in the future. In particular, this research provides a deeper comprehension of natural disaster frequency, which is, to the best of our knowledge, not previously investigated. Though we can not draw any clear conclusions, we detect weak signs of a positive effect on political trust with low frequency, and a negative effect with high frequency.

Significant coefficients of the control variables from the main FE model are, for the most part, in accordance with prior research on determinants of trust. For instance, Cook & Gronke (2005) look at trust in government, and find that a placement to the right on the political scale has a negative effect on political trust compared to the left side, which is the same findings as in this study, though the coefficient in our study is insignificant. Coefficients of gender and education are not significant in either of the analyses, nor in a study from Christensen and Lægreid (2005), although the signs show the same trend in all three studies. On the contrary, more attendance in religious services has a significantly positive effect on trust according to Cook & Gronke (2005), while the effect in our study was negative. Additionally, as previously stated, Albrecht (2017a) has conducted the research that is most similar to ours, and findings in her paper agrees with the results from the study at hand. Based on the latter, comparing this study to other findings such as Cook et al. (2005), Christensen et al. (2005), and Albrecht (2017a) indicates, despite some variation in the results, that the analysis and findings of this thesis are reliable.

As presented in the literature review in section 2.2.2, scholars argue whether trust can be affected in the short term, or if trust is more stable over time and only will be influenced on a long-term perspective. We previously assumed in this study that short-term external factors, such as natural disasters, can influence political trust. However, since we do not have sufficient evidence that natural disasters influence political trust, we can question if our assumption holds. On the one hand, it might be that natural disasters just in general do not have impact political trust. On the other hand, it could be that political trust does not get affected by short-term external factors, and that trust therefore is relatively constant over time, which is why we find little effect on political trust. There are, however, some weak effects observed at low frequencies for meteorological and climatological disasters. Yet, hydrological disasters are not statistically significant at any level. We do not see a reason why (at least not through intuition or relevant literature) hydrological disasters should affect political trust any differently than meteorological or hydrological. In essence, there are two possible reasons for this; endogeneity issues through measurement error or omitted variable bias. By excluding important variables that explain a non-insignificant variance in political trust, the effect will be added to independent variables in the model and bias the coefficients. We do not think that this is the case if we look at what current literature says about known factors to affect political trust (Albrecht, 2017a). Nevertheless, it would be interesting to compare the magnitude between the subgroups. However, different measurements (e.g. km^2 and kph), as well as the lack of observations, makes this challenging. The duration of the different disaster types is, on the other hand, comparable. As seen in Table A.3 in the appendix, meteorological disasters have on average a substantially shorter duration than the other two subgroups, which is interesting when knowing that meteorological disasters show more indication of a potential effect on political trust compared to hydrological disasters.

We mentioned bias coming from measurement error in, among others, section 5.2, which might be the biggest uncertainty regarding the model and consequently our analysis. The EM-DAT data are lacking when it comes to reporting dead, affected and damages, as well as the magnitude of the different natural disasters. There is bias created from the measurement error since the resulting bias always leads to a smaller absolute value. Variance is the average *squared* deviation from the mean, so sufficient measurement error might shift the weight of the coefficients towards other regressors (Abel, 2017). There is a possibility that the weak statistical significance at low frequency values is a result of shifted bias, and that both climatological and meteorological disasters have no real effect on political trust even at low frequencies. Alternatively, they do have a real effect, and so do hydrological disasters, but the bias has masked the statistical significance in the model. This is also where any causal claim hinges, and suspected bias through measurement error will effectively negate any claim we can make about causal inference of weather-related natural disasters and frequency effects on political trust.

We should be concerned of the existence of other political aspects that affect political trust that is not controlled for in the model. By excluding these potential effects, endogeneity problems can arise through omitted variable bias. Central America, Mexico and Colombia is a region characterized by population growth and economic development. However, the countries are not unfamiliar with corruption, political instability and high crime rates (The BBC NEWS, 2018). When investigating the time lines for the countries of interest, there are several noteworthy political events in the region between 2004 and 2014 (The BBC NEWS, 2018). First, we emphasize that there are several political events that might have affected political trust in a negative way. For instance, political leaders have been arrested for corruption in several countries, such as in Guatemala in 2005 and 2008, Costa Rica in 2009, Panama in 2010 and El Salvador in 2014. Additionally, the demand of two hours daily propaganda on TV and radio in Honduras in 2007, followed by an economic depression the next year, are factors that may have influenced the perception of political performance. Nevertheless, there are also episodes that are likely to have increased political trust. Specific examples on this are that the government in Costa Rica voluntarily started aiming to become the first carbon neutral country in 2007, and three years later, they elected their first female president. Another factor that is not controlled for in the regression model is media coverage. Scholars have discussed media coverage to be a source of influence on the perception of political performance (Albrecht, 2017b). For instance, negative media coverage of politicians after a natural disaster occurrence might have an effect on the citizens understanding of the political situation, and therefore impact individual perception and trust towards politicians. This way, empirical research might have a tendency to overestimate the results, and we can therefore wonder if this is the case in our study as well, that our research findings have been affected by the media. An ideal strategy would control for this in the regression model, nevertheless, LAPOP does not provide us with sufficient data on media coverage for the region of interest in our study periods.

A broad range of researchers agree that climate change is influencing both the frequency and the magnitude of weather-related natural disasters. The increasing trend of weather-related natural disasters from 1950 to this date is illustrated in Figure F.9. In particular, hydrological and meteorological disasters have experienced a significant growth in frequency. Climatological disasters have caused tremendous consequences, such as the occurrence of over two years of dramatic wildfires in California, and a water crisis in South Africa in 2018 after several years of drought (Vercammen, 2018; Dludla, 2018). Even in Norway, new weather records have frequently been reached in recent years (Bjørnæs, 2008). In fact, climate change is a heated political topic, with a variety of opinions and thoughts related to it. Some politicians deny the existence of it, while others have climate change as their main political cause. That said, the United Nations have put climate change on the agenda with their 17 sustainability goals. The UN Sustainable Development Goals are the worlds common plan to exterminate poverty, fight inequality and stop climate change within 2030 (The United Nations, 2008).

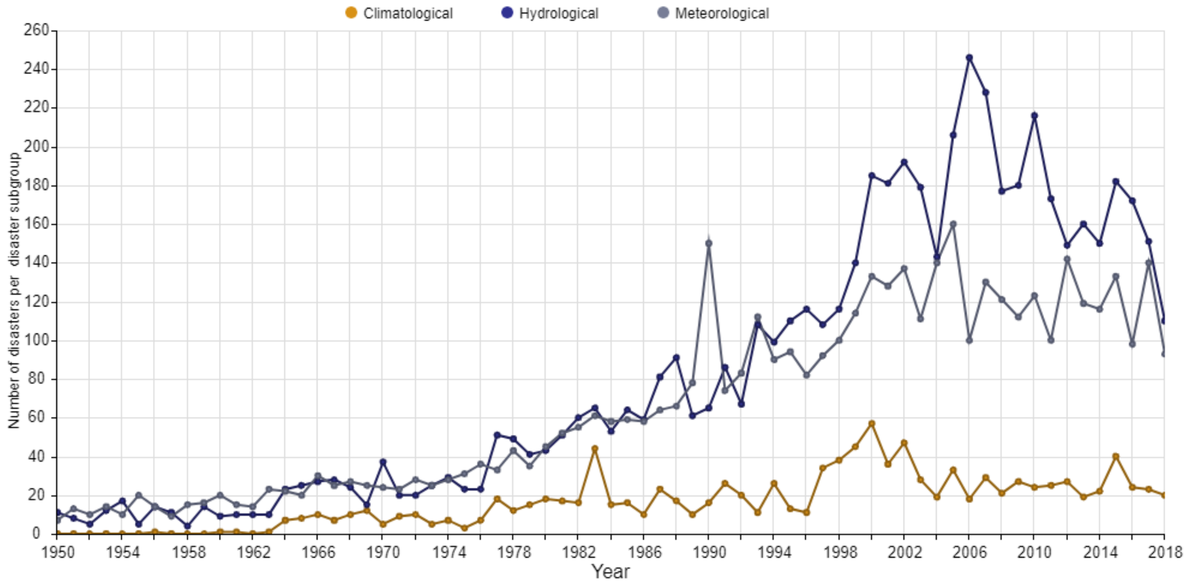

Figure F.9: Weather-Related Natural Disaster Frequency 1950-2018 (EM-DAT, 2018)

7.2 Policy Implications

With increased disaster frequency and magnitude, it is reasonable to assume that natural disasters will be an even bigger concern in the future, both politically and among citizens. Climate change can affect the perception of politicians, and with increased awareness of climate change, the politicians can expect stricter demands for good climate change policies in the future. By example, clever climate change mitigation policies and good disaster management can potentially increase political trust. Therefore, political awareness on climate change and natural disasters is essential. Even so, to get a broad agreement that climate change is a fact, and that the world needs to act together in order to reach the desired UN Sustainable Development Goals before the tipping point (the point of no return), have shown to be challenging to say the least (Enuka, 2018; Fouré & Bellora, 2018).

According to our findings, it appears as if trust is not a sufficient incentive for a politician to implement better disaster policies (as political trust does not seem to be overly affected by natural disasters). Nevertheless, this does not implicate that politicians should not be more prepared ex ante. In fact, there are other reasons for politicians to implement improved climate change mitigation and better natural disaster management. Disaster consequences, such as human suffering and damaged infrastructure, incentivize good disaster policies. Long-run considerations of policy implications could start by conducting a detailed and thorough sustainable strategy plan for the next decades. The goal for this plan should be how to implement cost-effective policy-making in the Central America area, with the attempt to prevent an increase in natural disaster frequency. In addition, it would be an idea to invest in new research and technology on natural disasters. Technology develops along an exponential curve, and it is realistic to assume that more knowledge on disasters can improve disaster management and reduce disaster vulnerability in the future.

8 Concluding Remarks

This study employs a fixed effects model on panel data to analyze the impact and frequency of weather-related natural disasters on political trust in the long run. The region of interest is Central America, Mexico and Colombia. The findings reveal that neither weather-related natural disaster events nor the frequency of said events have sufficient statistical evidence to conclude they are affecting political trust. There is a weak negative exponential correlation between natural disaster frequency and political trust in the frequency dummies, indicating a trend that more disasters are correlated with less political trust. There is also weak statistical evidence suggesting that provinces that experience a low frequency of natural disasters have slightly higher political trust than provinces that do not. Any causality is difficult to claim however, as there is a substantial possibility of bias through measurement error in the EM-DAT data.

As a last remark, we want to emphasize that as weather-related natural disasters are becoming more frequent and severe, more research should be conducted to better prepare for future disasters and their consequences. Especially, there are conducted few studies over several countries that analyze the effects of natural disasters on political trust, as well as a lack of literature on natural disaster frequency. More research investigating this could provide policy makers and politicians with a better understanding of the political consequences of natural disasters and how to earn the trust of the population.

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A Appendix

A.1 Distribution and Normality of Dependent Variable

As seen in Figure A.1, the dependent variable *Political Trust* is normally distributed, both illustrated in the distribution plot to the left, and the normal probability plot to the right.

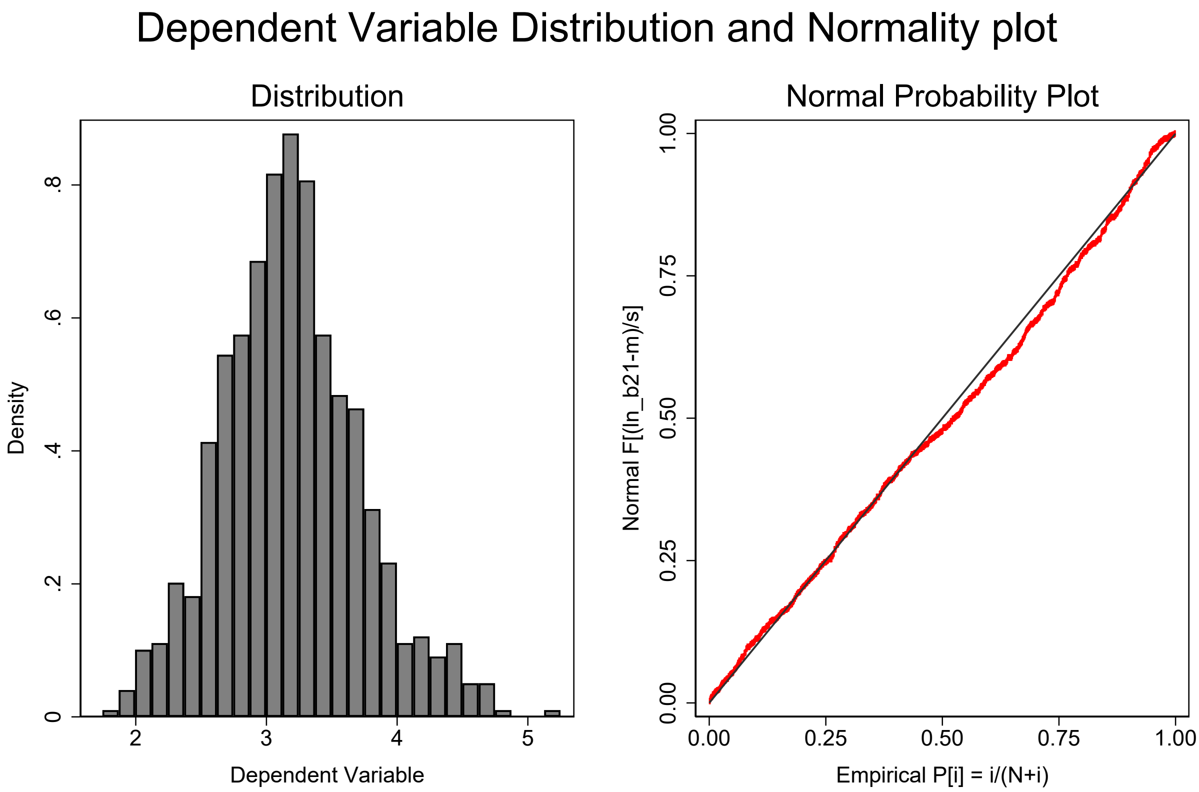

Figure A.1: Distribution and Normality of Dependent Variable

A.2 Descriptive Statistics of Control Variables

Descriptive statistics of control variables in the main regression model is shown in Table A.2.

Table A.2: Descriptive Statistics of Control Variables

	Count	Mean	SD	Min	Max
Political Trust	792	3.188838	.5339465	1.744681	5.25
Occurrence	792	1.481061	1.251909	0	6
Total Deaths Weighted	792	4.365819	14.64349	0	113.3836
Total Affected Weighted	792	19535.22	36492.86	0	198307
Total Damage Weighted	792	7906.655	24484.65	0	160745.9
Duration	792	76.97727	153.7365	0	1414
Duration^2	792	29530.57	118755.1	0	1999396
Education	792	7.713383	1.799762	3.06383	12.19444
Age	792	38.31233	2.601668	30	56.69444
Age^2	792	1474.595	205.1282	900	3214.26
Male Ratio	792	.4953629	.0259254	.3606557	.625
ln GDP	792	8.280195	.7101667	6.995313	9.456208
Ideological Scale	792	5.954607	.883743	2.857143	9.611111
Support in Political System	792	4.644346	.6160455	2.488372	6.266667
Trust in Local Government	792	4.214574	.575019	2.25	6.85
Religious Attendance	792	2.443215	.4889684	1.307692	4

A.3 Descriptive Statistics of Natural Disaster Subgroups

Table A.3 presents descriptive statistics of hydrological, meteorological, and climatological natural disasters, with their corresponding magnitude and duration, as well as data on total affected, deaths and damages.

Table A.3: Descriptive Statistics of Natural Disaster Subgroups

	Count	Mean	SD	Min	Max
Hydrological	792	.8674242	.9744392	0	5
Meteorological	792	.4356061	.7615241	0	6
Climatological	792	.1780303	.4021084	0	2
Hydrological Magnitude	792	54891.35	197009.6	0	1212796
Meteorological Magnitude	792	11.625	48.22639	0	425
Climatological Magnitude	792	0	0	0	0
Hydrological Duration	792	36.7298	84.68578	0	362
Hydrological $Duration^2$	792	8511.705	25645.55	0	131044
Meteorological Duration	792	2.491162	8.396762	0	70
Meteorological $Duration^2$	792	76.62247	455.1642	0	4900
Climatological Duration	792	37.75631	130.9492	0	1341
Climatological $Duration^2$	792	18551.57	108412.5	0	1798281
Total Deaths Hydrological Weighted	792	1.820532	3.156267	0	14.88713
Total Deaths Meteorological Weighted	792	2.528239	14.53804	0	113.3836
Total Deaths Climatological Weighted	792	.0170484	.1059867	0	.6751165
Total Affected Hydrological Weighted	792	8406.57	16900.81	0	98989.05
Total Affected Meteorological Weighted	792	1697.495	6048.496	0	35479.14
Total Affected Climatological Weighted	792	9431.155	33817.86	0	190866.2
Total Damage Hydrological Weighted	792	3114.148	16045.98	0	160745.9
Total Damage Meteorological Weighted	792	4446.552	18483.66	0	155555.6
Total Damage Climatological Weighted	792	345.9547	3701.378	0	51229.51

A.4 Description of Variables

A description of the variables from the main regression model will now be presented. The phrasing of the questions asked in the survey interviews, used to measure the LAPOP variables, with their corresponding response scale, is included.

Table A.4: Description of Variables
(EM-DAT, 2018; LAPOP, 2018; The World Bank, 2018)

Variable Name	**Explanation of Variable**	**Response Scale**
Political Trust	To what extent do you trust the political parties?	1=Not at all 7=A lot
Ideological Scale	According to the meaning that the terms "left" and "right" have for you, and thinking of your own political leanings, where would you place yourself on this scale?	1=Left 10=Right
Support in Political System	To what extent do you think that one should support the political system of (country)?	1=Not at all 7=A lot
Trust in Local Government	To what extent do you trust the local or municipal government?	1=Not at all 7=A lot
Religious Attendance	Meetings of any religious organization? Do you attend them...	1=Once a week 2=Once or twice a month 3=Once or twice a year 4=Never
Trust in the Justice System	To what extent do you trust the justice system?	1=Not at all 7=A lot
Occurrence	Measure of disaster frequency.	
Total Deaths Weighted	The sum of dead and missing, weighted with country population in millions.	
Total Affected Weighted	The number of total injured, homeless and affected, weighted with country population in millions.	
Total Damage Weighted	The economic consequence measured in 1000 US dollars, weighted with country population in millions.	
Duration	Days of the occurrence of a disaster event.	
Magnitude	The scope of disaster event, measured in km^2 or kph.	
Education	Mean of years attended at school over province.	
Age	Mean age over province.	
Male Ratio	Male/Female ratio expressed on a range from [0,1].	
ln GDP	GDP per capita in US dollars, ln-transformed.	

A.5 Correlation Matrix Part 1

Table A.5: Correlation Matrix 1

	Coefficient
	Political Trust
Occurrence	0.0632***
Total Deaths Weighted	0.102*
Total Affected Weighted	-0.0407
Total Damage Weighted	0.0346
Duration	-0.00474
Duration^2	-0.0306
Education	0.00345
Age	0.116*
Age^2	0.120*
ln GDP	0.154*
Male Ratio	0.00254
Ideological Scale	0.189*
Support in Political System	0.407*
Trust in Local Government	0.473*
Religious Attendance	0.139*
	Occurrence
Total Deaths Weighted	0.306*
Total Affected Weighted	0.249*
Total Damage Weighted	0.272*
Duration	0.331*
Duration^2	0.200*
Education	0.0246
Age	-0.148*
Age^2	-0.145*
ln GDP	0.00144
Male Ratio	0.0873**
Ideological	-0.0218
Support in Political System	0.0403
Trust in Local Government	0.0178
Religious Attendance	-0.0189
	Total Deaths Weighted
Total Affected Weighted	0.0890**
Total Damage Weighted	0.536*
Duration	-0.00345
Duration^2	-0.0211
Education	-0.122*
Age	-0.198*
Age^2	-0.191*
ln GDP	-0.151*
Male Ratio	0.0140
Ideological Scale	-0.0651***
Support in Political System	-0.0595***
Trust in Local Government	0.0514
Religious Attendance	-0.166*
Observations	792

*** p<0.1, ** p<0.05, * p<0.01

A.6 Correlation Matrix Part 2

Table A.6: Correlation Matrix 2

	Coefficient
	Total Affected Weighted
Total Damage Weighted	0.114*
Duration	0.496*
Duration^2	0.308*
Education	-0.238*
Age	0.0698**
Age^2	0.0681***
ln GDP	-0.240*
Male Ratio	0.0456
Ideological Scale	-0.0242
Support in Political System	-0.0208
Trust in Local Government	0.0423
Religious Attendance	-0.233*
	Total Damage Weighted
Duration	0.000917
Duration^2	-0.00712
Education	0.00133
Age	-0.00930
Age^2	-0.00852
ln GDP	-0.00848
Male Ratio	-0.0261
Ideological	-0.0700**
Support in Political System	0.0887**
Trust in Local Government	0.112*
Religious Attendance	-0.141*
	Duration
Duration^2	0.866*
Education	-0.0672***
Age	-0.0216
Age^2	-0.0252
ln GDP	-0.0437
Male Ratio	0.0912**
Ideological	-0.0172
Support in Political System	0.0184
Trust in Local Government	-0.0577
Religious Attendance	-0.153*
Observations	792

*** $p<0.1$, ** $p<0.05$, * $p<0.01$

A.7 Correlation Matrix Part 3

Table A.7: Correlation Matrix 3

	Coefficient
	Duration^2
Education	-0.0991*
Age	0.0194
Age^2	0.0159
ln GDP	-0.0229
Male Ratio	0.0485
Ideological Scale	-0.0884**
Support in Political System	-0.0229
Trust in Local Government	-0.0769**
Religious Attendance	-0.156*
	Education
Age	0.0277
Age^2	0.0239
ln GDP	0.527*
Male Ratio	0.0687***
Ideological Scale	0.0645***
Support in Political System	0.148*
Trust in Local Government	-0.151*
Religious Attendance	0.296*
	Age
Age^2	0.997*
ln GDP	0.422*
Male Ratio	0.0333
Ideological Scale	-0.0475
Support in Political System	0.229*
Trust in Local Government	0.0810**
Religious Attendance	0.105*
	Age^2
ln GDP	0.411*
Male Ratio	0.0298
Ideological Scale	-0.0389
Support in Political System	0.225*
Trust in Local Government	0.0793**
Religious Attendance	0.103*
Observations	792

*** $p<0.1$, ** $p<0.05$, * $p<0.01$

A.8 Correlation Matrix Part 4

Table A.8: Correlation Matrix 4

	Coefficient
	ln GDP
Male Ratio	0.0923*
Ideological Scale	0.0210
Support in Political System	0.282*
Trust in Local Government	-0.0495
Religious Attendance	0.321*
	Male Ratio
Ideological Scale	0.0228
Support in Political System	-0.00602
Trust in Local Government	-0.0459
Religious Attendance	0.0956*
	Ideological Scale
Support in Political System	0.251*
Trust in Local Government	0.222*
Religious Attendance	0.163*
	Support in Political System
Trust in Local Government	0.470*
Religious Attendance	0.117*
	Trust in Local Government
Religious Attendance	-0.0258
Observations	792

*** p<0.1, ** p<0.05, * p<0.01

A.9 Omitted Variable and Sign Change

Table A.9: Omitted Variable and Sign Change

	(1) Political Trust	(2) Political Trust
Occurrence	0.00074	-0.00458
	(0.01710)	(0.01701)
Religious Attendance		0.09279*
		(0.05162)
ln GDP	0.35719**	0.31744*
	(0.16847)	(0.17468)
Year Fixed Effects	√	√
Province Fixed Effects	√	√
Clustered SE over Province	√	√

Notes: No variables change significantly or have notable change in the coefficients with the exception of Occurrence and ln GDP. Significance level denoted * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.