THE UNIVERSITY OF NEW SOUTH WALES

SCHOOL OF ECONOMICS

HONOURS THESIS

Trust & Institutional Confidence in the Aftermath of Disaster

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October 28, 2016

DECLARATION

'I declare that this thesis is my own work and that, to the best of my knowledge, it contains no material that has been published or written by another person or persons, except where due acknowledgement has been made. This thesis has not been submitted for award of any other degree or diploma at the University of New South Wales or at any other institute of higher education.'

Rohan Garga

October 28, 2016

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my supervisors, Dr. Gautam Bose and Dr. Peter Kriesler, for all your guidance and patience over the last year. Your input has been invaluable and I truly have learnt so much from you throughout this time. This thesis would not have been possible without your help. I keenly look forward to continuing our work in the future.

I would also like to sincerely thank the faculty of the School of Economics who have provided me with suggestions, feedback and motivation throughout this year. In particular, I'd like to thank Dr. Sarah Walker, Dr. Pauline Grosjean, Dr. Tess Stafford & Dr. Gigi Foster for their help. A mention must go out to Dr. Ilan Noy at the University of Wellington, thankyou for generously sharing your data and advice.

Thankyou to my family for always encouraging me and allowing me the freedom to pursue my goals. Without your support I would have not be the person I am today. This thesis is as much the product of my your work as it is mine.

I'd like to thank my friends, both here and abroad, who have helped keep me sane throughout this year. A special shoutout must go to Martin, I will fondly remember our compelling coffee chats. Finally, a big thankyou to the 2016 Honours cohort for all the laughs and banter during the tough times!

ABSTRACT

This thesis investigates how natural disasters can lead to changes in the level of societal trust and institutional confidence in an affected population. Using empirical methods and two in-depth case studies, I find that OECD regions generally experience a fall in both the levels of societal trust and institutional confidence following disaster, whilst Non-OECD regions record a sizeable increase in trust and confidence. I provide evidence that these changes in trust and confidence tend to persist over time, whilst also showing that different types of disaster events have distinct impacts in shifting attitudes.

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1 INTRODUCTION

Over the last two decades, the study of trust and social capital has garnered increased attention, with a general acceptance that greater cooperation amongst individuals translates into more efficient markets and functioning of institutions. Over this same period, in the face of accelerating climate change, there has been a concerted effort in investigating the economic and social impacts of natural disasters. This thesis examines the possibility that large natural disasters can lead to changes in the levels of societal trust and institutional confidence in an affected population. I seek to show how these effects differ across populations with varied economic, class and ethnic compositions as well as across different types of disaster events. Finally, I analyse whether these changes in societal trust and institutional confidence are short-lived or tend to persist over time.

The literature on trust and social capital is large and varied, stretching from economics to sociology. Putnam et al. (1993, p. 167) provides the earliest thoughts on social capital, associating it with "features of social organisation, such as trust, norms, and networks that improve the efficiency of a society by facilitating coordinated actions". Measuring generalised trust is one way to gauge the level of social capital in a population. An element of trust is inherent in virtually all economic activity that relies on the future actions of others (Arrow, 1972), with these transactions in high-trust environments accomplished at a lower cost. Over time, high-trust societies develop norms of civic cooperation, "behaviours that resolve prisoner's dilemmas without imposing substantial external costs" (Knack & Keefer, 1995), indicating that the channels exist for any changes in trust, perhaps due to a disaster event, to persist over time.

Amartya Sen's (1981) seminal *Poverty and Famines*, laid the foundation for modern economic thought surrounding natural disasters by demonstrating that the impacts of disasters are determined by the social and political characteristics of the devastated region and not purely a function of the physical magnitude of the disaster. The disaster literature has since focused primarily on investigating the indirect costs that disasters inflict upon an economy. Cross-country studies have tended to concentrate on macroeconomic changes, such as GDP, investment and inequality (Albala-Bertrand 1993; Noy 2009). This thesis advances this strand of research with a particular focus on attitudinal shifts following large natural disaster events.

A priori, it is hard to know how an affected population would respond in the aftermath of a large disaster, and if these responses are temporary. Populations with stronger institutions may have high expectations of an effective formal institutional response in the aftermath of a large natural disaster. If rates of institutional confidence fall after disaster, this would indicate a failure of formal institutions to meet this population's pre-disaster expectations. The opposite would be true when considering populations with weaker institutions, they would have much lower expectations of a formal institutional response eventuating, and thus even a small response could translate into higher levels of institutional confidence. This same intuition applies to societal trust, populations with higher levels of pre-disaster trust may have high expectations regarding the general trustworthiness of individuals, and a fall in the aftermath of disaster indicates that this expected behaviour was not met. This thesis seeks to clarify the nature and persistence of these relationships.

My analysis is based on the sample of countries included in the World Values Survey (WVS) between 1980 and 2014, from which I extract responses on societal trust and institutional confidence. I match this survey data with natural disaster events from the Emergency Events Database (EM-DAT). From this combined dataset, I conduct both a cross-country and sub-national regional empirical analysis, utilising primarily a selection on observables approach. The nature of this sample allows me to identify the impact of a large natural disaster on an affected populations level of societal trust and institutional confidence, as well as investigating whether this impact persists over time.

The disaster literature holds that social and economic stratification plays a role in the preparedness, response and recovery of disaster events (Bolin 1998; Wisner et al., 2004). To understand this dynamic I analyse how disaster impact differs across populations with varied compositions. For example, do societies with greater income inequality or increased ethnic heterogeneity hold different expectations of societal trust or institutional response in the aftermath of disaster? As well as estimating heterogenous treatment effects, I provide two case studies of large disasters, Hurricane Katrina & The Indian Ocean Earthquake and Tsunami. These cases help illustrate how the stark differences in institutional setting influenced expectations of the societal and institutional response during the aftermath of disaster.

Khan (2005) shows that different types of disasters tend to impact macroeconomic outcomes in distinct ways. *Geophysical* disasters, which are extremely deadly and damaging, may come with different expectations of societal and institutional response when compared against *Meteorological* and *Climatological* disasters, which are not as deadly but tend to displace relatively more people. When placed in the context of accelerating climate change, disentangling how different types of disasters affect expectations of a societal and institutional response become important when considering both *ex ante* mitigation and *ex post* assistance policy prescriptions.

The remainder of this thesis is subsequently organised in the following chapters. Chapter 2 provides a review of the relevant literature on trust, natural disasters and the intersection of the two, whilst Chapter 3 describes common strategies used in isolating and estimating causal effects in the trust and disaster literature. Chapter 4 discusses the data I gather and outlines the procedure applied in the generation of a merged dataset, with explicit acknowledgement of any limitations in the data. These limitations subsequently restrict the scope of empirical models that I can estimate, which are set out in Chapters 5 & 6. Chapter 5 focuses on the cross-country relationship between annual disaster intensity and a country's average level of societal trust and institutional confidence. Chapter 6 takes this one step further, and analyses the relationship between *large* natural disasters and trust at a regional/provincial level. Heterogenous treatment effects and the persistence of trust changes are also presented. Chapter 7 illustrates these mechanisms by presenting two case studies, Hurricane Katrina & The Indian Ocean Earthquake and Tsunami. A discussion of these findings are provided in Chapter 8, finally followed by an overview and possible future extensions of this research in Chapter 9.

2 LITERATURE REVIEW

This chapter presents a review of the literature relevant to my research, split into three sections. The first section introduces the idea of trust and social capital and provides reasons as to the economic importance of these concepts. These are broadly split into three primary points; the formation of markets, the functioning of institutions and it's role as a type of informal insurance mechanism. Secondly, the literature on natural disasters is discussed, starting with the measurement and trends of disaster events. This is followed by the indirect short and long-term costs that disasters inflict upon economies. Finally, literature on the intersection between societal trust, institutions and natural disasters is presented.

2.1 CONCEPTUALISING TRUST

The notion of social capital has popped up throughout history under different guises with varied definitions, making it one of the more difficult economic concepts to pin down. Composed of diverse relationships and engagements, the elements of social capital are conglomerate and clustered and, in many instances intangible. The most famous early thoughts on social capital came from Putnam et al. (1993, p. 167) who associated it with 'features of social organisation, such as trust, norms and networks that can improve the efficiency of a society by facilitating coordinated actions'. A later conception is provided by Christoforou (2013, p. 719) who states that social capital 'identifies with norms and networks of cooperation, reciprocity and trust that facilitate collective action for the achievement of a mutual benefit'. Both these definitions and countless similar others (Bowles and Giantis, 2002; Coleman, 1988; Bordieu, 1986), have at their core the notion that social capital sprouts from a set of group characteristics, such as a shared identity and social obligations that coalesce for wider public benefit.

Taking social capital to mean the ability of people to associate and form interpersonal networks, is analogous to asking the fundamental question, 'under what contexts can individuals be assured that the promises they have made to one another are credible?' (Dasgupta, 2005 p. S3). The answer is when they *trust* each other. The circumstances out of which trust arises are varied and contemporaneous, tending to penetrate through all layers of interaction. Trust is cultivated by incentivising cooperation in the following situations;

Mutual Affection (where group members have interdependent utilities, so cooperation begets further utility), Pro-Social Disposition (where reciprocity within the group is a social norm) and using External Enforcement (for example through formalized contracts). Trust is maintained in all these scenarios through the threat of punishment, and by this mechanism trust becomes a social norm (Dasgupta, 2005). Seabright (1997) supports these channels of trust creation through empirically demonstrating that cooperation engenders further cooperation.

But how do these channels of trust diffuse throughout society? Putnam et al. (1993, pp. 168-169) states that 'mutual trust is lent. Social networks allow trust to become transitive and spread: I trust you, because I trust her and she assures me that she trust you'. Expanding on this line of thought, Elsner & Schwardt (2013) propose a model to explain how cooperative interactions at the micro level can develop into generalised trust amongst the wider population. Catalysed by the instrument of 'preferential mixing' whereby individuals have the agency to associate with whoever they want, Elsner & Schwardt (2013) explain that overlapping and emerged platforms of networks allow people to experience cooperative behaviour beyond their immediate network. Trust within one's immediate network is known as contextual trust, and is distinct from generalised trust where one develops a trusting outlook on any possible future interaction partner (Yamagishi & Yamagishi, 1994). Contextual trust habituates a general society and internalises expectations of cooperative behaviour (Mengel, 2009; Gintis, 2004) stimulating trustworthy responses in kind, effectively strengthening and maintaining a network of generalised trust.

By measuring trust levels at every interaction layer, we are able to determine the strength of the networks that link these agents, and hence able to approximate the stock of social capital within these layers. At the micro level, measuring contextual trust between individuals in small groups allows us to determine that particular group's inventory of social capital. Similarly, measuring generalised trust throughout an economy estimates its level of social capital. Within the literature, generalised trust has been used to measure related concepts, such as morality, social cohesion & societal capability (Tabellini, 2008; Easterly et al., 2006; Najeeb, 2007, 2009).

2.2 EMPIRICAL WORK ON TRUST

There is a large body of empirical work on trust and social capital across a variety of disciplines. This section provides a thorough analysis of this work with a particular focus on the role of trust in driving the following economic phenomena; market formation and cooperation, functioning of institutions and risk sharing. These three phenomena are crucial in both *ex ante* and *ex post* disaster settings.

2.2.1 *Markets & Economic Cooperation*

Economic activities that require individuals to rely on the future actions of others are conducted at a lower cost in high-trust environments (Knack & Keefer, 1997). Arrow (1972, p. 357) confirms this need for mutual confidence, stating *"Virtually every transaction has within itself an element of trust, certainly any transaction conducted over a period of time"*. These transactions are the building blocks of any economy and include the exchange of products for future payment, employment contracts as well as all investment and savings decisions. Agents that exist in economies where mutual trust is high spend less resources in protecting themselves from hazardous transactions. Moreover, agents are able to make production and investment decisions optimal over the long run, engendering relatively more productive economic activity. Dasgupta (2005) concludes that market formation and social capital cultivation are complementary processes, imposing fewer costs to transactions and inherently reducing information asymmetry amongst rational agents.

High-trust societies are characterised by norms of civic cooperation (Putnam 1993). Knack & Keefer (1995, 1997) define civic norms as behaviours that resolve prisoner's dilemmas without imposing substantial external costs on other parties. Coleman (1990) notes that the costs and benefits of cooperating and defecting in these prisoner's dilemmas are determined by the socially-driven internal (e.g. guilt) and external (e.g. shame and ostracism) sanctions. Examples of cooperative norms range from the relatively simple, such as littering to prime features of a functional society, such as the enforcement of property rights. From an economy wide standpoint these norms improve allocative efficiency, reducing the costs of monitoring and enforcement when information asymmetry does exist, thereby raising the payoffs of investment (Young, 2007).

2.2.2 *Functioning of Institutions*

Group social dynamics, such as the level of trust, have been shown to strongly predict a range of outcomes, which in turn influence the institutions and macroperformance of an economy. There have been a range of studies (Easterly et al., 2006; La Porta et al., 1997) demonstrated that well-functioning institutions are often observed in countries where individuals have a greater tendency to trust one another. Tabellini (2008) reasons that there are three channels by which norms of generalised trust lead to well-functioning institutions; law enforcement is easier because citizens are more likely to be law-abiding; bureaucrats are more likely to refrain from corruption; and voters are more inclined to vote based on general social welfare. Of course the literature is beset with examples that demonstrate how institutional capacity and positive growth are strongly correlated (Acemoglu 2001, 2003 ; Knack and Keefer, 1995; etc). Putnam (1993) finds strong evidence of this, showing that regional governments in the higher-trust areas in the north of Italy provide public services with greater efficacy than governments in the less-trusting south. Similarly, Narayan and Pritchett (1999) discovered that in a sample of 50 villages in Tanzania, households in communities where there is greater participation in village-level social organisation on average enjoy higher income per head.

Dasgupta (2005) provides a simple and convincing quantitative model of how social capital can contribute to macroperformance. Consider a standard production function $Y = A f(K, L, H)$ where A is total factor productivity and K, L, H denotes aggregate physical, labour and human capital. Contemplate a scenario where the economy shifts from an equilibrium system of non-cooperation beliefs to one where cooperation is the norm. There are two channels by which this shift could manifest itself. High-trust societies, where contracts are enforced, are incentivised to accumulate physical and human capital as the returns on these behaviours are large (Knack & Keefer 1997, La Porta et al. 1997). The second channel is when the externalities of trusting behaviour are economy wide, providing greater incentives to innovate and invest, reflected in increases in total factor productivity.

2.2.3 *Risk Sharing*

Communities that exist in an equilibrium of high levels of trust are less dependent on formal institutions to enforce agreements (Knack & Keefer, 1997). Prominent examples of these systems include informal credit markets dependent on strong interpersonal trust or securing property rights and contract enforcement when no such authority exists (or is unable to provide them). External shocks, such as large natural disasters, have the ability to completely disrupt the functioning of formal institutions. In these contexts affected communities with strong levels of trust are able to limit the costs of external shocks and return relatively quickly to normal societal functions (Udry 1994).

Beaman & Magruder (2012) echo this sentiment, explaining that in the absence of formal institutions, individuals use network links to improve risk sharing and insure themselves against idiosyncratic shocks. These networks form the basis of generalised trust and in the event of a large natural disaster can be drawn upon to assist in the aftermath and recovery process. In essence, affected population with higher levels of trust can fall back on these social bonds as an informal insurance mechanism. Feigenberg et al. (2013) demonstrate the role trust and social capital takes on in the absence of formal institutions. They show that the low default rates of microfinance institutions can be well-explained by the social capital that was built up through repeated interactions with their peers. This was achieved as the usual mechanisms for lenders – either collateral or joint-liability contracts – were not used, leaving social capital (in the form of cooperation) as the only variable that could explain for the substantial improvements in risk sharing throughout the community.

2.3 THE DIRECT IMPACT OF NATURAL DISASTERS

Pelling et al. (2002) provides a generally accepted classification of disaster impacts, distinguishing between direct and indirect impacts. Direct impacts include the mortality and displacement as a consequence of a disaster, as well as damages to fixed assets, capital and raw materials. As is common in the literature, I use these direct impacts (Killed, Affected, Damage) to estimate the effect on indirect outcomes, such as societal trust and institutional confidence.

2.3.1 *Measurement*

Most empirical work on natural disasters stems from the Emergency Events Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disasters (CRED). The database is compiled from UN agencies, non-governmental organisations, insurance companies, research institutions and press agencies. CRED defines a disaster as a natural situation or event which overwhelms local capacity, necessitating a request for external assistance.

For an event to be included in EM-DAT at least one of the following criteria must be satisfied: (1) 10 or more people reported killed; (2) 100 people reported affected; (3) declaration of a state of emergency; or (4) call for international assistance (Vos et al., 2009). The disasters covered include *hydro-meteorological* (floods, wave surges, storms, droughts, landslides and avalanches), *geophysical* (earthquakes, tsunamis and volcanic eruptions) and *biological* (epidemics and insect infestations).

EM-DAT reports the number of people killed, the number of affected, and the dollar amount of direct damages in each disaster (Cavallo & Noy, 2011). [1] Importantly, the database does not report the physical magnitude (Richter scale, Wind speed, Storm surge water level, etc.) of each disaster.

The metrics described above provide a measure of the immediate impacts as a result of a natural disaster. There has been a recent offshoot in the literature which attempts to determine the longer term impact of a disaster by aggregating and transforming the conventional metrics. Noy's (2016) 'Lifeyears' Index is such an example of aggregate disaster intensity measures. The basic premise behind the use of the Lifeyears Index is to provide a truer representation of total disaster intensity across the world. To achieve this the value of human life is considered equal everywhere, while the value of monetary damages is not. For example, a dollar lost in the highest-income country in the EM-DAT dataset (Luxembourg) exerts less of an adverse impact on society than a dollar lost in a country where financial resources are far more scarce, such as Somalia.

The Lifeyears Index takes the following form (Noy 2016):

$$Lifeyears = L(M, A^{death}, A^{exp}) + I(N) + DAM(Y, P)$$

where $L(M, A^{death}, A^{exp})$ is the number of years lost due to event mortality, calculated as the difference between the age of death and life expectancy. $I(N)$ is the cost function associated with people who were injured, or otherwise affected by the disaster. $DAM(Y, P)$

1 The number of people killed includes "persons confirmed as dead and presumed dead"; people affected are those "requiring immediate assistance during a period of emergency, i.e., requiring basic survival needs such as food, water, shelter, sanitation, and immediate medical assistance."

accounts for the number of human years lost as a result of the damage to capital assets and infrastructure.

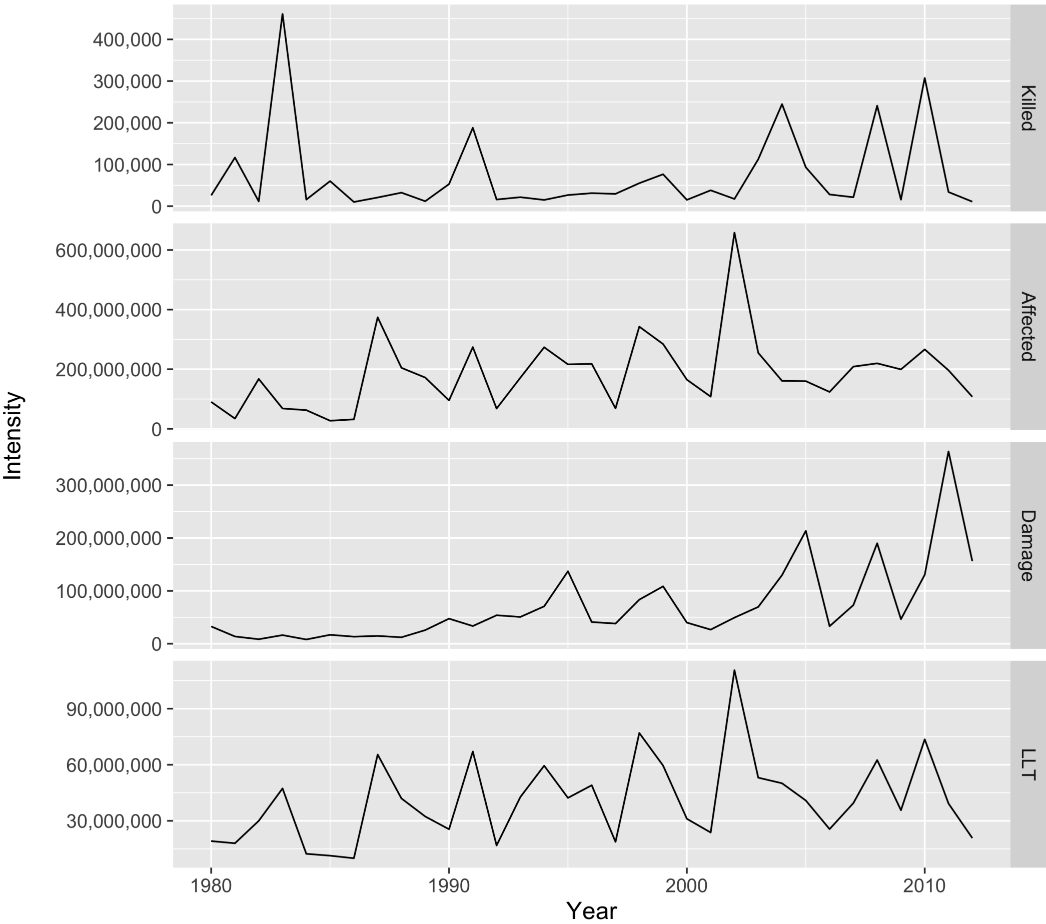

Figure 1: Natural Disaster Time Series

Figure 1 reveals the annual worldwide trends of disaster intensity since 1980, sorted by disaster variable. It is clear that the three measures commonly used in the measurement of immediate disaster impacts follow differential trends, demonstrating the usefulness of an aggregate disaster measure which can more fully account for these differences. As I am interested in examining the *immediate* impacts on a population, I do not use the Lifeyears Index in my empirical analysis as it is a measure of the longer-term impacts of disaster.

2.3.2 *Trends*

The incidence of natural disasters has been increasing over time for every region in the world (Cavalho & Noy, 2011). In the Asia-Pacific region, the incidence has grown from an average of 11 events per country in 1970s to over 28 events in the 2000s. Other regions show a similar upward trend. The direct impacts defined above are also heterogenous across countries, with the vast majority of people killed and affected by disasters being in developing countries. For the period 1970-2008, 96% of people killed and 99% affected were in the Asia-Pacific region, Latin America and the Caribbean or Africa (Cavalho & Noy, 2011). Noy (2009) notes that there may exist an inflation of disaster measures in lower-income countries to exert pressure on donors for increased aid.

Catastrophic natural disasters, such as the 2010 Haitian Earthquake, are associated with a much greater impact, even compared to 'large' disasters. The 2010 Haitian Earthquake destroyed more than 100% of the value of GDP, and killed approximately 2.4% of the national population. There has been recent evidence that the occurrence and intensity of these large natural disasters are increasing, with Mei & Xie (2016) finding that landfalling typhoons in East and Southeast Asian countries have increased in intensity by 12-15% since 1980. Moreover, the proportion of storms of categories 4 and 5 have at least doubled. The authors conclude that these changes are tied to enhanced ocean surface warming and that there is evidence that all global regions are experiencing similar trends.

2.4 THE INDIRECT COSTS OF NATURAL DISASTERS

The indirect costs of natural disasters are the economic activity that ceases to take place following a disaster and subsequently due to it. This notably includes the production of goods and services, the loss of income at a household level and the destruction of human and social capital. These indirect costs arise due to direct damage of physical infrastructure, the extra resources used during the rebuild and outmigration away from disaster stricken areas. The literature has typically tended to account for the indirect impacts through region-specific aggregate measures, such as GDP, consumption, investment, trade and inequality measures. Moreover, the literature tends to split up costs between the short run (usually up to three years after the event) and the long run (minimum of five years after the event).

2.4.1 *Short-run Economic Effects*

The first foray into analysing the short run economic impacts of large disasters was conducted by Albala-Bertrand (1993), who collected data on 28 disasters in 26 countries during 1960-1979. Albala-Bertrand (1993) found that GDP increased by 0.4%, inflation was unchanged, capital formation was higher whilst agricultural and construction output increased in years of large disasters. Whilst Albala-Bertrand (1993) used simple before-after differences, more recent papers have tended to use the following econometric framework:

$$(1) \quad Y_{i,t} = \alpha + \gamma DIS_{i,t} + \beta X'_{i,t}, + \epsilon_{i,t}$$

In model 1, $Y_{i,t}$ denotes an impact measured after disaster (e.g. GDP per capita), $DIS_{i,t}$ measures the disaster's instantaneous impact on region *i* at time *t*. This variable can either be a binary indicator of disaster occurrence or an indicator of magnitude using physical measures (Richter scale, Wind speed, etc.) or direct impact (such as number of killed or affected). $X'_{i,t}$ denotes a vector of control variables that affect the dependent $Y_{i,t}$, potentially including a lagged dependent term $Y_{i,t-1}$.

Model 2 below allows for the investigation of country-specific interactions with disaster impact (Cavallo & Noy, 2011). The coefficients of interests are γ and ϕ:

$$(2) \quad Y_{i,t} = \alpha + \gamma DIS_{i,t} + \beta X'_{i,t} + \phi DIS_{i,t}.V_{i,t} + \lambda V_{i,t} + \epsilon_{i,t}$$

Through the use of this framework Raddatz (2007, 2009), Noy (2009) and Hochrainer (2009) conclude that natural disasters, particularly large climatic events, have an adverse impact on short-term output. Moreover, regions with higher per capita income, literacy rates, government spending and openness to trade are better able to withstand the shocks of natural disasters. Raddatz (2009) also suggests that aid flows have had little impact in modulating consequent output shocks.

Rodriguez-Oreggia et al. (2009) use flood data at the level municipal in Mexico to find that poverty increases between 1.5%-3.6%, whilst HDI declines in disaster-affected municipalities. Neumayer & Plümper (2007) find that women and girls tend to be more vulnerable than men in the aftermath of disasters, whilst Evans et al. (2010) show that strong storm events have a negative effect on fertility rates.

2.4.2 *Long-run Economic Effects*

Compared with the short-run effects, the literature on long-run growth effects is sparse and inconclusive, mainly due do the difficulty in constructing appropriate counterfactuals with any accuracy. Noy & Nualsri (2007) find evidence of contractionary disaster effects in the long run, whilst Skidmore & Toya (2002) find generally expansionary effects in the long-term. Skidmore & Toya (2002) suggest that disasters can speed up the Schumpeterian process of ’creative destruction’, allowing for the replacement of old infrastructure with more productive capital. Cuaresma et al. (2008) test this notion, but find evidence that only high-income countries, particularly those with strong institutions are able to rebound in this manner.

2.5 social trust, institutions & disasters

2.5.1 *Social Vulnerability*

Social vulnerability centers on the role of social and economic stratification in relation to natural disasters (Cutter et al., 2003). It emphasises the various ways in which social systems function, and the resultant effect on the capacity of a person or group to anticipate, cope with, and recover from a disaster (Wisner et al., 2004). One possible mechanism by which communities may fragment following disaster is through sociocultural ‘disintegration’. Leighton (1959) suggests that destructive events effectively tear the social fabric within communities, disrupting social norms and weakening support structures. A society with depressed integration systems are at risk of further fragmentation from future disasters (Dynes, 2002; Quinn, 2006).

Existing fault lines in a population, driven through the vulnerability of marginalised communities, provide avenues through which a large natural disaster can deepen existing inequalities. Hurricane Katrina provides an example of the consequences disasters can impact, with the socially vulnerable pockets of New Orleans bearing the largest impacts in both the short and long-term (Oliver-Smith 2006). The ability of formal institutions to respond in a timely and effective manner - a fundamental characteristic contributing to a region’s vulnerability - can have the effect of smoothing over and modulating any simmering civil unrest (True, 2016).

The most common method used in quantifying social vulnerability is the hazards-of-place model, developed by Cutter et al. (2003). Factor analysis of macro socioeconomic and demographic data reveals the following variables as crucial in determining social vulnerability; county-level wealth, age structure, density of the built environment, housing stock and tenancy, the racial and ethnic composition, the occupational structure, and infrastructure dependence (Meyer et al., 2008).

2.5.2 *The Role of Institutions*

Recent literature has begun to explore the relationship between initial direct costs of disasters and the institutional structures of a region. In a survey of the disaster literature Cavallo & Noy (2011) note that to evaluate the determinants of disasters most studies use model 3 below as a baseline:

$$(3) \quad DIS_{i,t} = \alpha + \beta X'_{i,t} + \epsilon_{i,t}$$

where $DIS_{i,t}$ measures direct damages of a disaster in country *i* at time *t*. As noted in 2.3.1 direct damages are gauges of the instantaneous impact of natural disasters, and include metrics such as mortality, morbidity and capital losses. The vector $X'_{i,t}$ denotes the control variables of interest. These tend to include an agnostic measure of disaster intensity (Richter scale, Wind speed, Rainfall, etc.) as well as variables that capture the institutional and geographic vulnerability of the region to disasters.

Khan (2005) provides strong evidence of the inverse correlation between rates of economic development and amount of direct disaster costs, despite both high-income and low-income countries experiencing similar levels and intensity of disasters. In 1990, a poor country (GDP per capita less than \$2000) on average experienced 9.4 deaths per million people per year, whilst a rich country (GDP per capita greater than \$14 000) experienced only 1.8 deaths as a result of disasters. Khan (2005) posits that the difference is likely to due to the greater amount of resources available to be spent on prevention and mitigation, such as building codes, land-use planning and engineering interventions.

Several studies (Khan 2005, Skidmore & Toya 2007, Strömberg 2007) find that stable democratic regimes and the greater security of property rights tend to reduce the direct costs of natural disasters. Similarly, Anbarci et al. (2005) show that inequality is important in determining the success of disaster mitigation efforts. In a similar vein, studies find that the freedom of the press (in both journalistic licence and distribution of media) plays an important role in limiting the costs of disasters. Besley & Burgess (2002) find that flood impacts in India tend to be negatively correlated with the distribution of newspapers, whilst Eisensee & Strömberg (2007) provide similar evidence for the US.

2.5.3 *Trust as Informal Insurance*

As presented above, formal institutions can play a key role in the aftermath of disaster. However, in the absence of an appropriate institutional response, communities with established networks are able to limit the costs of external shocks by drawing on reserves of social trust to assist one another. Boyd & Richardson (1995) theorise that when information acquisition is costly or imperfect, like during times of large disaster, agents revert to heuristic social norms to guide their actions. Thus, individuals in disaster-vulnerable populations use network links and societal trust as a means to improve risk sharing and effectively becomes a mechanism of insurance against idiosyncratic shocks (Udry, 1994).

The strength of these networks and the degree of societal trust are dependent upon the characteristics of a region. Tabellini (2008) & Najeeb (2009) find strong evidence for the relationship between levels of education and trust. Apart from increasing the stock of human capital, education may build social capital through shrinking social distance within communities. Moreover, economic empowerment has been shown as a robust cross-country determinant of social distance and trust (Zak & Knack, 2001; Uslaner, 2002). There is a strong body of work that show how existing social cleavages inherent within a population translate into a lack of social cohesion and generalised trust (Easterly & Levine 1997, Alesina et al. 2003, Nunn & Wantchekon 2011). Bjørnskov et al. (2010) find that institutional and historical factors are significant in the analysis of trust and social capital. In populations that lack strong societal trust, for one of the reasons above, also lack the insulating properties of trust as a means of collective risk-sharing.

3 THE IDENTIFICATION OF CAUSAL EFFECTS - COMMON STRATEGIES

Empirical analysis is centred on identifying associations that can confirm or reject a theoretical hypothesis. To that end, this chapter will specify empirical strategies used commonly in the literature with the aim of confirming hypothesis *on the causal relationships between natural disasters and trust*.

Chapter 4 describes the data I am able to gather, with explicit acknowledgement of its limitations. These data limitations subsequently restrict the scope of empirical models that I can estimate, which are set out in Chapters 5 & 6.

3.1 IDEAL DATA STRUCTURE

The gold standard for empirical confirmation of a causal hypothesis is data resulting from a randomised control trial. This would involve subjecting a treatment group to a large natural disaster and comparing against a control. Assuming the experiment was well randomised and that the natural disaster affects all respondents equally, we can estimate an average treatment effect (ATE). This ATE represents the causal effect of a natural disaster on the trust levels in a region.

Clearly this is not a feasible scenario and as such we rely on observational data to produce estimates with a causal interpretation. Ideally, the structure of this observational dataset would be a repeated panel of representative respondents across sub-national regions. Data would be disaggregated at the local community level. An example of the ideal level of disaggregation is shown in Figure 2, which shows the affected regions following Hurricane Katrina.

3.2 SELECTION ON OBSERVABLES

Causal inference in a selection on observables design relies on the assumption that we control for all confounding factors, so that potential outcomes are independent of the

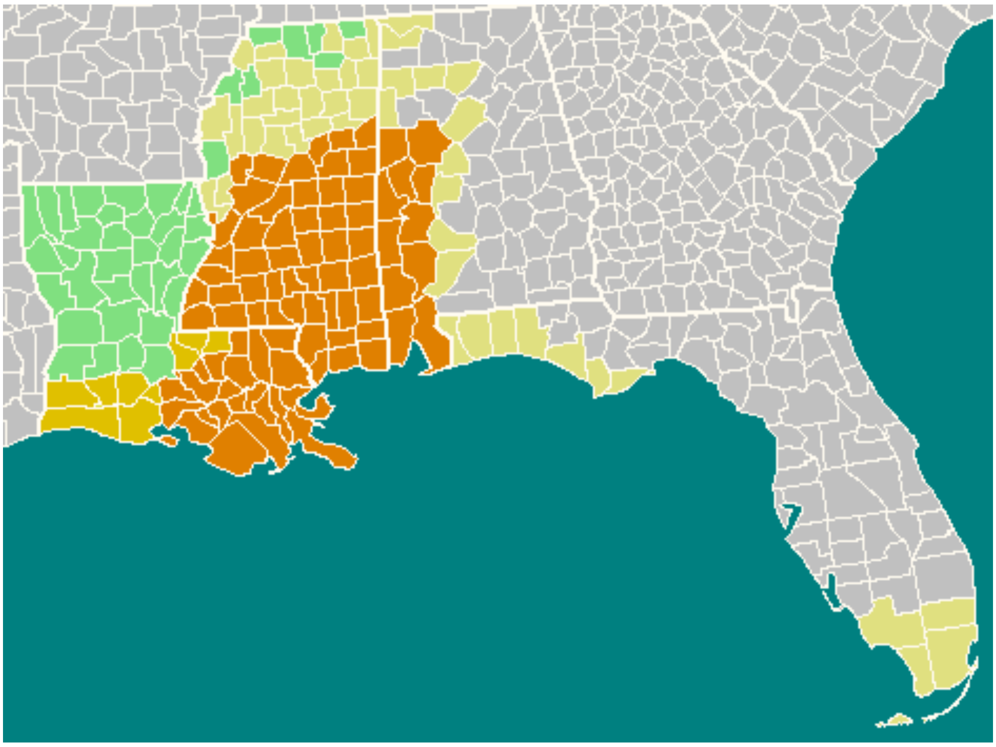

Figure 2: Hurricane Katrina Affected Regions

treatment conditional on observable covariates. In this case we attempt to isolate 'good' variation in the intensity of a natural disaster by controlling for 'bad' variation. 'Good' variation is understood as variation in the treatment that is considered 'as good as randomly assigned', whilst 'bad' variation is variation in treatment that is correlated with the outcome. Consider the following linear model:

$$\mathrm{trust}_k = \beta \mathrm{DisasterIntensity}_k + \gamma X'_k + \epsilon_k$$

where k indexes a sub-national region area. The dependent variable trust_k denotes a measure of trust or confidence amongst a regional population. Measurements include:

(1) Generalised Trust - the proportion of the population in region k that agree they trust most people in their society.

(2) Civic Norms - A scalar indicating the degree to which individuals in region k adhere to socially constructive civic norms.

(3) Institutional Confidence - the proportion of the population in region k that agree they have confidence in a vector of institutions (Law Enforcement, Armed Forces, Civil Services, Parliament, Religious Institutions)

$\mathtt{DisasterIntensity}_k$ is a measure of the direct impact of a natural disaster on region k. Section 2.3.1 provides greater detail of the measurement and trends of these direct impacts. Briefly, direct impacts attempt to capture the immediate consequences of a natural disaster on an affected populations. Measures include:

(1) Disaster type (Earthquake, Cyclone, Drought, etc.)

(2) A scalar variable measuring physical disaster intensity (Richter Scale, Rainfall, Windspeed, etc.)

(3) Number of people Killed

(4) Number of people Affected

(5) Standardised Damage Value $\left[\frac{\text{Amount of Damage}}{\text{GDP per capita}}\right]$

X'_k represents a vector of observed covariates specific to region k. As noted above, the assumption underlying a SOO design is that we observe all the factors that affect treatment assignment and correlated with the potential outcomes. This assumption is untestable and is certainly too strong to hold without conditioning, creating a selection bias issue. The following section is used to detail the methods employed in the literature to address this selection bias. Controlling for the disaster vulnerability of a region is analogous to controlling for factors that affect treatment assignment. The following covariates have been commonly used in the literature to control for a populations disaster vulnerability:

(1) Economic - Average Education, Income/GDP per capita, Unemployment Rate, Openness to Trade, Income inequality

(2) Social - Ethnic, Language, and Religious Fractionalisation

(3) Institutional strength - Legal, Political & Press freedoms, Post-Communism

(4) Geographic - Population Density, Proximity to common physical triggers (such as large bodies of water or fault lines)

(5) Total Value of Foreign Aid Contributed

Economic empowerment has been shown as a robust cross-country determinant of social distance and trust (Zak & Knack, 2001; Uslaner, 2002). To control for this, GDP per capita, Unemployment and Income Inequality are used as a proxy for the relative economic standing of a region. Tabellini (2008) & Najeeb (2009) find strong evidence for the relationship between levels of education and trust. Apart from increasing the stock of human capital, education may build social capital through shrinking social distance within communities.

Glaeser et al. (2000) find that a person's religious beliefs are significant in the prediction of trusting behaviour, with Feigenberg et al. (2013) arguing that the religiosity of a person is a direct channel which influences the quantity and distance of social ties to members of their community.There is a strong body of work that show how existing social cleavages inherent within a population translate into a lack of social cohesion and generalised trust (Easterly & Levine 1997, Alesina et al. 2003, Nunn & Wantchekon 2011). Controls for these social characteristics include the Ethnic, Language and Religious Fractionalisation Indexes of these populations. Bjørnskov et al. (2010) find that institutional and historical factors are significant in the analysis of trust and social capital. Finally, Khan (2005) shows that geographic characteristics of a region are strongly related to the disaster vulnerability of the population.

3.2.1 *Matching Estimators*

As noted above, for a SOO research design to have causal inference the practitioner must assume that the treatment is as good as randomly assigned after conditioning on X'_k or risk selection bias. To strengthen the validity of the unconfoundedness assumption one can employ matching estimators. Matching estimators ensure that the levels of treated and control units similar baseline covariates, X'_k. Conditioning on the vector of covariates X'_k leads to the treatment being as good as randomly assigned, allowing for causal inference. I use propensity score matching in Chapter 6 to condition on the vector of observed covariates X'_k set out above.

3.3 Selection on Unobservables

As the SOO identifying assumption is untestable, it is advisable to consider Selection on Unobservables designs. The premise underlying a SOU design is the identification of some subset of 'good' variation in the treatment, whilst discarding the remaining variation. This subset of 'good' variation can then be used to estimate the treatment effect. Whilst the identifying assumptions in a SOU setting are more plausible, one would also expect less precise estimates as well as a reduced ability to make general statements on the average treatment effects.

3.3.1 *Difference-in-Differences*

The difference-in-differences (DID) approach mimics the randomisation in social experiments by observing differences following a treatment event (policy shift, natural disaster) for one group and not another. It achieves this by analysing data with a time dimension to control for unobserved but fixed omitted variables. Strongest identification would result from panel data although the identification is also possible with representative repeated cross-sections. By comparing the outcome variable before and after the natural disaster for both the control and treated regions, an estimated disaster effect can be generated. The main assumption underlying the DID model is that the regions must have similar trajectories between the measurement of the disaster (Angrist & Pischke, 2009).

A generalisation of the DID approach is through the use of time and group fixed effects. Identification is based on obtaining within group time variation, which are group specific changes over time.

3.3.2 *Regression Kink Discontinuity*

Regression discontinuity (RD) models are a type of quasi-experimental designs where the probability of receiving a treatment is a discontinuous function of one or more underlying variables (Cameron & Trivedi, 2009). In the case of a natural disaster, say an earthquake, one can use a physical measure, say distance to the epicentre, as the selection variable. Those individuals or regions further away from a distinct cutoff do not receive treatment and thus constitute the controls, whilst those closer to the epicentre are the treatment units. These selection variables can apply to a range of disasters, such as total rainfall for large storms or consecutive days above a threshold temperature for droughts. Identification occurs when you take the sample of observations close to the cutoff point and measure the difference in outcome variables across these two groups. As observations within these two groups are expected to be very similar to one another it is possible to estimate an average treatment effect.

4 DATA

4.1 WORLD VALUES SURVEY

4.1.1 *Dependent Variable - Generalised Trust & Civic Norms*

For social capital to be an economically useful concept, its stock should be measurable and quantifiable (Solow 1995; Christoforou 2012). To facilitate measurement, the literature has mainly employed two approaches. The first uses survey indicators to directly measure levels of generalised trust amongst a population. The second approach uses observable behaviour to measure other aspects of social capital, like civic activities (Najeeb 2009). This second approach stems from Putnam's (1993) seminal work in explaining the stark differences in effectiveness of regional governments in the north and south of Italy. Prominent examples of civic activities include measures of newspaper readership, voter turnout at referenda, membership in non-profit associations, and the diffusion of preference votes in elections.

I use both of these approaches to obtain a more whole measure of social capital, although focus primarily on generalised trust. This data are extracted from the full sample (6 Waves, 1980-2014) of the World Values Survey (WVS). These series provide in excess of 300,000 respondents and are designed to enable a cross-country comparison of values and norms. In most countries, stratified multistage random probability sampling was used with the intention of obtaining nationally representative samples (Inglehart et al., 2000). Inglehart (2000) notes that some groups - for instance, the better-educated and those in urban areas - are likely oversampled in most countries, especially in less developed countries. To correct for this I use the weight variable provided in the data, consistent with the literature (Knack & Keefer 1997, Bjørnskov et al. 2010).

The question used to measure the level of trust in a society is, *"Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people?"* My trust indicator (GENTRUST) is calculated as the percentage of respondents replying "Most people can be trusted", after eliminating "I don't know" responses (Knack & Keefer, 1997).

My second approach to quantifying social capital involves constructing a variable to measure norms of civic cooperation. Respondents were asked whether each of the following behaviours "can always be justified, never be justified or something in between".

(a) "claiming government benefits which you are not entitled to"

(b) "avoiding a fare on public transport"

(c) "cheating on taxes if you have the chance"

Respondents select a number from 1 (never justifiable) to 10 (always justifiable). These scales were reversed so that larger values indicate greater cooperation, and an aggregate CIVIC variable was constructed with a 30-point maximum. A higher CIVIC value reflects the individual's willingness to provide cooperative solutions to common prisoner's dilemmas with few or no costs to non-players (fellow members of society). Knack & Keefer (1997) point out that respondents are likely to be reluctant to admit to cheating governments, taxpayers or other people which likely means we have a substantial measurement error in our CIVIC variable. Moreover, changes in civic norms represent changes in cooperative behaviour amongst a population, and is likely a slow moving process (Young, 2007). For these reasons, I center the majority of discussion around changes in generalised trust.

From Table 1 we can see that GENTRUST has a mean of 0.269 whilst CIVIC has a mean of 25.641 across the full sample. Table 2 provide these summary statistics split by whether the individual resided in a country with OECD status. Whilst CIVIC values are broadly similar across samples, values of GENTRUST differ markedly. 33.4% of those in OECD countries tend to trust, whilst only 23.5% of those in Non-OECD countries responding that most can be trusted. These figures are consistent with the literature (Easterly et al. 2006, Tabellini 2008, etc.)

Table 1: Dependent Variable Summary Statistics: Full Sample

Variable	N	Mean	St. Dev.	Min	Median	Max
GENTRUST	306,547	0.269	0.443	0	0	1
CIVIC	273,465	25.641	5.621	3	28	30
TRUST_CHURCH	300,262	0.670	0.470	0	1	1
TRUST_ARMY	293,371	0.644	0.479	0	1	1
TRUST_POLICE	296,739	0.551	0.497	0	1	1
TRUST_CIVIL	289,850	0.481	0.500	0	0	1
TRUST_PARLIAMENT	289,039	0.418	0.493	0	0	1

Table 2: Dependent Variable Summary Statistics: Split Sample

		OECD			*Non-OECD*	
Variable	N	Mean	St. Dev.	N	Mean	St. Dev.
GENTRUST	105,225	0.334	0.472	201,322	0.235	0.424
CIVIC	90,431	25.908	5.294	183,034	25.510	5.772
TRUST_CHURCH	102,533	0.521	0.500	197,729	0.747	0.435
TRUST_ARMY	100,812	0.635	0.481	192,559	0.648	0.478
TRUST_POLICE	102,215	0.628	0.483	194,524	0.511	0.500
TRUST_CIVIL	100,735	0.456	0.498	189,115	0.494	0.500
TRUST_PARLIAMENT	101,341	0.368	0.482	187,698	0.444	0.497

4.1.2 *Dependent Variable - Institutional Confidence*

Similar to the measurement of social capital, I measure institutional confidence using responses from the WVS. Respondents were asked to rate their confidence in each of the following institutions (Variable names are in brackets):

(a) "The Churches" - (`TRUST_CHURCH`)

(b) "The Armed Forces" - (`TRUST_ARMY`)

(c) "The Police" - (`TRUST_POLICE`)

(d) "The Civil Service" - (`TRUST_CIVIL`)

(e) "The Parliament" - (`TRUST_PARLIAMENT`)

Answers were coded from 1 (A great deal) to 4 (None at all). To allow for comparison with GENTRUST these scales were transformed into a binary variable. 0 denotes "No Confidence" (previously coded as 3 & 4) whilst 1 denotes "Confident" (previously coded as 1 & 2).

The first three institutions (Churches, Armed Forces, Police) are typically first-respondents in disaster situations and play instrumental roles in the following relief efforts. The last two variables (Civil Service, Parliament) are a broader measure of the effectiveness of formal institutions in conducting everyday activity crucial to the functioning of societies.

Some of these institutions are trusted similarly in both OECD and Non-OECD nations, such as the Armed Forces and the Civil Services. However there is considerable divergence in the confidence in the Church, the Police and the Parliament across OECD and Non-OECD populations.

4.1.3 *Individual Covariates*

A number of additional variables were extracted from the WVS with the intent to control for individual characteristics that affect levels of trust. These included Age, Sex dummy, Religious dummy, Relative Income, Education level and Satisfaction (Nunn & Wantchekon 2011, Glaeser et al. 2000, etc.). Table 3 provides the summary statistics for these individual covariates, split by OECD status. Most variables are similar between the two samples, except that respondents in Non-OECD countries tend to be much more *Religious* (76% v. 59%) but report lower levels of *Satisfaction*.

Table 3: All Covariates Summary Statistics

	OECD		Non-OECD	
Variable	Mean	St. Dev.	Mean	St. Dev.
Age	43.944	17.103	38.965	15.359
Sex	0.476	0.499	0.485	0.500
Religious	0.591	0.492	0.759	0.428
Income	4.706	2.457	4.542	2.249
Education	4.856	2.215	4.668	2.244
Social Class	3.170	0.907	3.390	1.019
Satisfaction	7.147	2.125	6.357	2.550
Gastil Index	1.469	0.757	3.893	1.646
Legal Quality	6.819	1.243	5.152	1.112
Ethnic Fractionalisation	0.269	0.206	0.456	0.224
Language Fractionalisation	0.222	0.169	0.409	0.307
Religious Fractionalisation	0.465	0.253	0.434	0.247
Postcommunist	0.199	0.399	0.230	0.421
Openness to trade	0.831	0.451	0.571	1.154
Investment Price Level	1.064	0.275	0.777	0.444
Gini Coefficient	36.193	7.860	41.029	10.518
GDP per capita	8,898.179	7,181.233	2,166.423	3,391.537

4.2 CROSS-COUNTRY CONTROLS

To control for differences across countries I use the variables specified in Bjørnskov et al. (2010) as a starting point and supplement with additional aggregate variables found to be significant in determining trust in previous works (Easterly & Levine 1997, Nunn & Wantchekon 2011). A full description and source can be found in Table 4 below, whilst summary statistics are reported in Table 3 above. Whilst most individual covariates are broadly similar across OECD and Non-OECD nations, there are significant differences in macroeconomic covariates. On average, OECD regions have superior institutions, lower fractionalisation, lower inequality and greater economic opportunity. Section 3.2 provides the justification for including these individual and cross-country covariates.

Table 4: Cross-Country Controls

NAME	SOURCE	DESCRIPTION
Gastil Index	Freedom House (2012)	Index capturing the existence of political rights and civil liberties; lower scores mean better protection of rights and liberties
Legal Quality	Fraser Institute (Gwartney et al., 2015)	Overall measure of the quality and capacity of the legal system, consisting of indices of judicial independence, impartiality of the courts, protection of intellectual property rights, and integrity of the legal system
Ethnic Fractionalisation	Alesina et al. (2003)	Index reflecting the probability that two randomly selected individuals from a population belong to different ethnic groups; higher scores indicate greater fractionalisation
Language Fractionalisation	Alesina et al. (2003)	Index reflecting the probability that two randomly selected individuals from a population belong to different language groups; higher scores indicate greater fractionalisation
Religious Fractionalisation	Alesina et al. (2003)	Index reflecting the probability that two randomly selected individuals from a population belong to different religious groups; higher scores indicate greater fractionalisation
Post Communist	World Bank (2015)	A dummy variable denoting whether a country is post-communist; 1 = post-communist
Openness to Trade	Penn World Tables (2014)	An index constructed by comparing shares of merchandise exports and imports
Investment Price Level	Penn World Tables (2014)	An index capturing the level of capital formation relative to USA GDP in 2005
Gini Coefficient	World Bank (2015)	Index measuring levels of income-inequality within a population
GDP per capita	World Bank (2015)	A measure of income levels per person across countries

4.3 VARIABLE OF INTEREST - NATURAL DISASTER INTENSITY

To measure the intensity of natural disasters and their direct impacts, I use an extension of the EM-DAT database collected by the Centre for Research on the Epidemiology of Disasters (CRED). The EM-DAT database contains data on the impacts of natural disasters from 1980 to 2012. For detailed information on the EM-DAT database please refer to section 2.3.1.

The EM-DAT database contains three measures of disaster intensity:

(a) The number of people killed (*Killed*)

(b) The number of people affected (*Affected*)

(c) The amount of direct damage measured in thousands of US dollars (*Damage*)

Previous literature has used these three variables as measures of immediate disaster impacts (Toya & Skidmore 2002, Khan 2005, Cavallo et al. 2013, etc.). Using simply one of these measures of disaster intensity does not capture the true effect that large disasters inflict on a population. For example, to only use *'Affected'* as an indicator would tend to exclude *Geophysical* disasters, which are extremely damaging and deadly, but affect fewer people than *Meteorological* or *Hydrological* disasters. Similarly, to only use *'Killed'* would tend to exclude those disasters which affect many people but are less deadly (such as *Climatological* disasters). To ensure that I am fully capturing the effects of large disasters on a population I consider all three measures when considering a treated population. Furthermore, I transform the *Damage* measure to a *Standardised Damage* value, simply by dividing the *Damage* by the GDP per capita of an affected population.

4.4 MATCHING PROCEDURE

My methodology and estimation are split over the following two chapters. Chapter 5 estimates the relationship between disaster intensity and a populations level of trust in a year on a sample of country-year observations. This sample was generated by combining the country-aggregated measures from the WVS with a repeated panel of yearly disaster measurements (Killed, Affected, Damage) for each country. The result was an unbalanced panel of 165 country-year observations between 1981-2012.

Chapter 6 analyses the relationship between a large natural disaster and the outcome variables at a sub-national or provincial level. An example of these regions include "New

England" or "Mid-Atlantic" in the US or "Sichuan Province" in China. Generally, this level of disaggregation is one level below the country and was chosen as it best preserved sample size (ie. Many countries in the WVS did not disaggregate further).

The natural disasters dataset used to match with the WVS was trimmed so that only disasters from 1990 onwards were considered. This trimming was conducted as the locations and impact measures in the EM-DAT database prior to 1990 have been deemed imprecise, on the advice of Dr. Ilan Noy, a leading authority on the economics of natural disasters. This left a dataset with 8 620 natural disasters between 1990 and 2012.

As I am only interested in the causal effect of a 'large' natural disaster on an affected population, I take the top 20 percent (Noy 2009, 2011) as measured by the direct impact (*Killed, Affected, Damage*). These disasters are marked as 'large' and are considered as treatment events. The survey data from the WVS do not contain the date of completion, only the year. This lack of information complicates the matching process; if I match a survey in year *t* to a survey in year *t*, there is no guarantee that the survey has been conducted *after* the disaster. To ensure I that I am empirically analysing trust and confidence after a large disaster, I match the sample of 2228 region-year observations from the WVS in year *t* to disasters in years *t-1*.

Most locations described in the disasters dataset mirrored exactly with a region from the WVS, and matching was trivial. When any locations did not mirror that of the WVS, a search using the *CIA World Factbook: Appendix F Cross-Reference List of Geographic Names* was conducted. All regions-year observations that were not matched up with a treatment were marked as controls. Resultantly, a sample of 2228 region-year observations between 1990 and 2012 was obtained.

For a disaster to be considered as large in my sample, it must have met at least one of the following criteria:

(1) 49 people killed

(2) 65 000 people affected

(3) Standardised Damage value of 6.75 (*The disaster with the SDV of 6.75 was a hurricane in the US that resulted in $85 000 000 US of damage*)

4.5 DATA LIMITATIONS

In Chapter 3 I identified that the ideal observational dataset from which to draw a causal inference would be a repeated panel of representative respondents across sub-national regions, ideally disaggregated to the local government level. Moreover, I set out the disaster measures and covariates that I would need in an ideal dataset. My data fails these criteria on the following accounts:

1. Not panel data
2. Data not disaggregated to the ideal level (WVS, Cross-Country Controls)
3. No data on the physical measure of disaster intensity (eg. Richter Scale, Wind Speed, Highest Water Level, etc.)
4. No data on the subsequent foreign aid flows following a large disaster

The structure of my data is repeated cross-sections of nationally representative samples. Panel data has the advantage of following the same individuals over time, ensuring that the practitioner is able to exactly control for idiosyncratic differences between observations.

This issue is complicated further by the disaggregation problem. Whilst the WVS attempts to collect nationally representative samples, I am primarily interested in sub-national regional analysis. To ensure that observations collected in the region-year sample is representative of its population, I exclude all observations that consisted of less than 20 individuals. As a result, the full sample of 2228 region-year observations was restricted to 1973 region-year observations. For the remainder of this thesis I make the strong assumption that each of these region-year observations is representative of the sub-national population from which it was gathered.

A further aggregation (or lack of disaggregation) problem is seen in the vector of cross-country controls described in Table 4. As there is sparse data on these variables at a sub-national regional level, I am forced to assume that all regions within a country are homogenous in these macro conditions. Moreover, the EM-DAT database contains no information on the physical measurement of disaster intensity. As these are purely exogenous values they would have proved useful when considering Regression Discontinuity or Instrumental Variable research designs. Finally, EM-DAT reports only sparse data on foreign aid flows for each disaster. As Nunn & Qian (2009) have shown, foreign aid can have major impacts on an affected population following a large external shock. I provide further evidence of this in Chapter 7 when examining how the influx of foreign aid played a role in the resumption of conflict in Sri Lanka but increased the peace dividend in Indonesia. It would have been useful to control for aid to isolate differences in trust as purely a function of the natural disaster.

5 METHODOLOGY & ESTIMATES I: COUNTRY AGGREGATES

I begin by plotting the basic relationship between the intensity of natural disasters in a year and a population's level of societal trust at a country level. Figure 3 plots the levels of generalised trust in country i in year t against the total number of people killed by disasters in country i in year t for OECD countries. Figure 4 plots the same relationship but for a sample of country-year observations in Non-OECD countries.

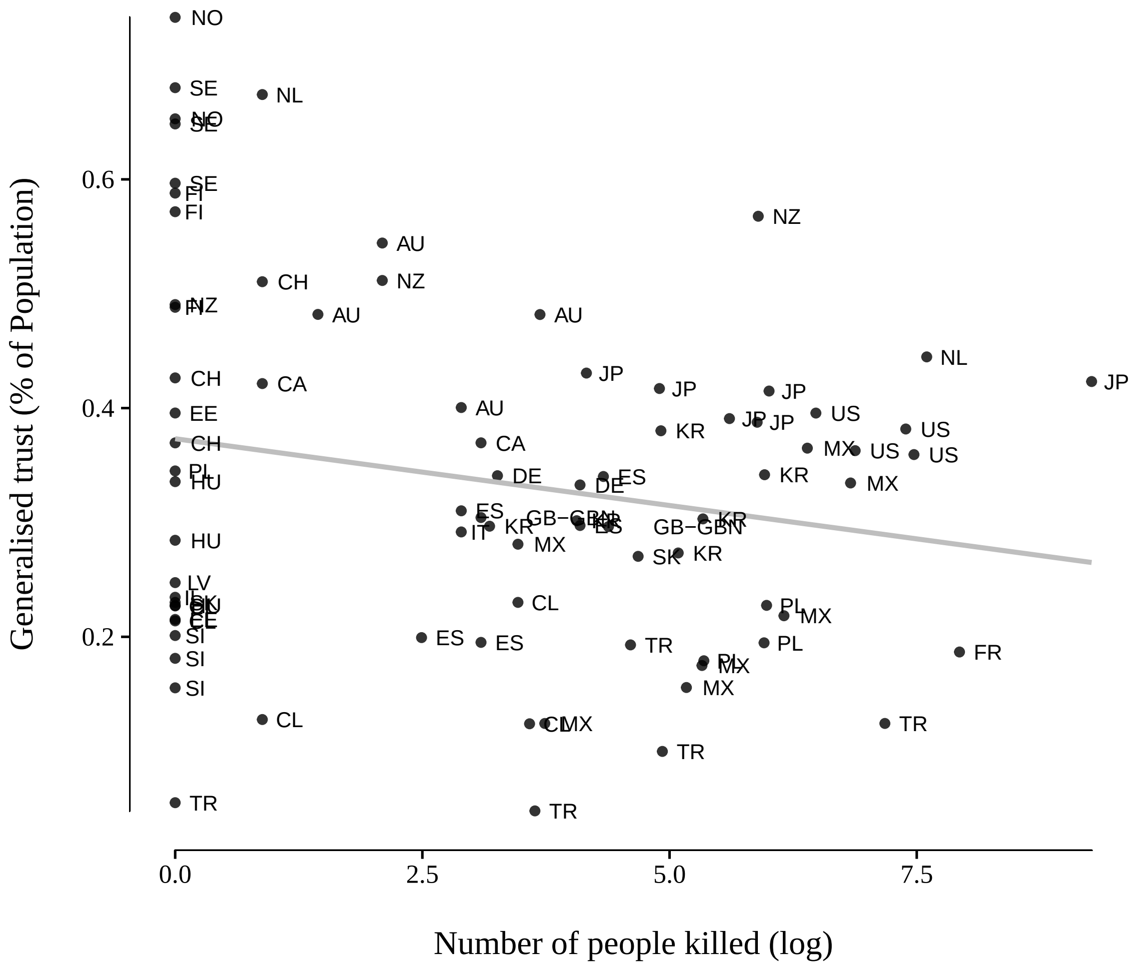

Figure 3: Generalised Trust and Disaster Intensity (Killed), OECD countries

Figure 3 shows that there is a negative correlation between the number of people killed and the levels of generalised trust in a OECD country. In contrast, Figure 4 shows the positive correlation of the same relationship in non-OECD countries. Together these figures foreshadow my main results described over the following two chapters. Chapter 5 frames

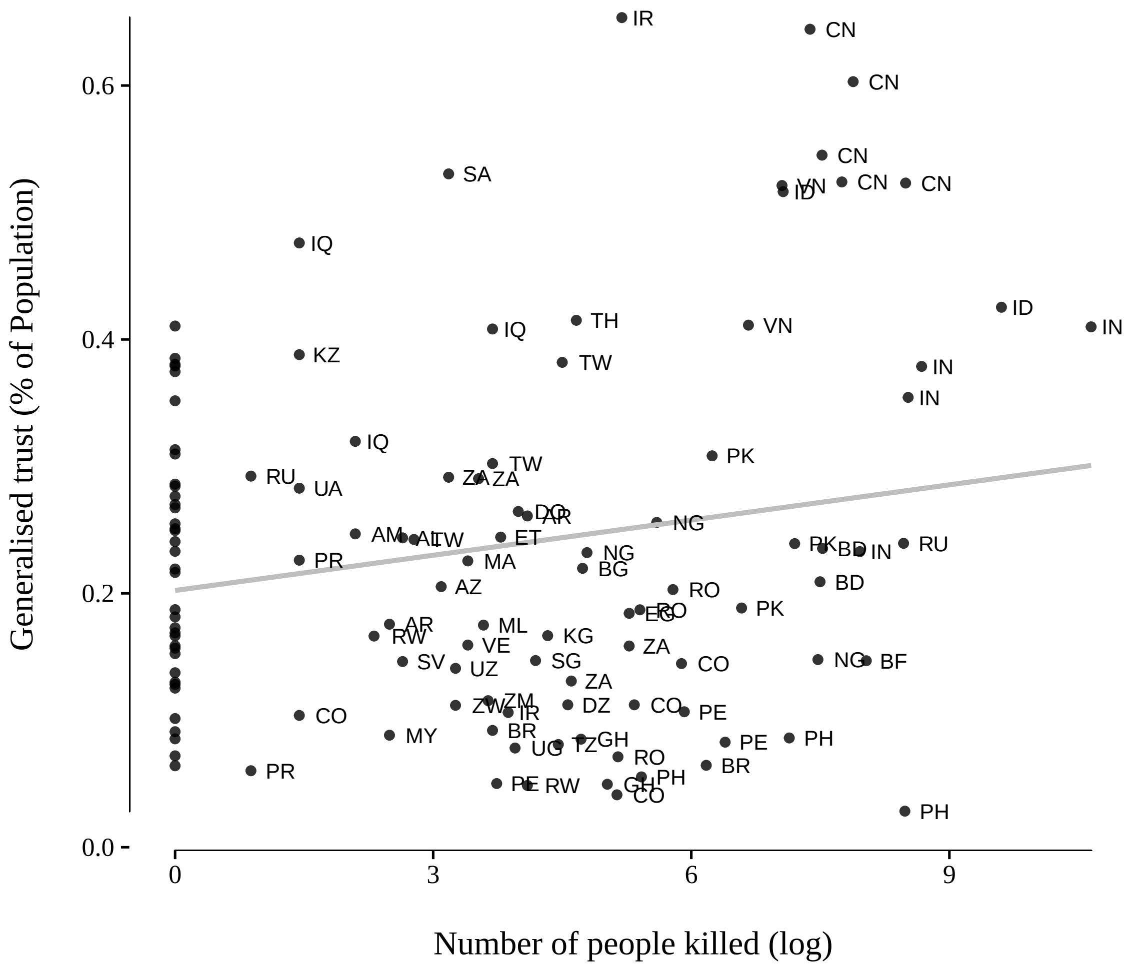

Figure 4: Generalised Trust and Disaster Intensity (Killed), Non-OECD countries

the analysis by focusing on the relationship between trust and disasters at the country level, whilst Chapter 6 builds on this inference though the use of disaggregated trust and disasters data at the sub-national level.

5.1 SELECTION ON OBSERVABLES

Consider the following pooled cross-sectional model:

$$(1) \quad \mathrm{trust}_{k,t} = \beta \mathrm{DisasterIntensity}_{k,t} + \gamma X'_k + \epsilon_{k,t}$$

where k indexes an aggregate country measure and t is time. The dependent variable $\mathrm{trust}_{k,t}$ denotes a vector of trust measures, $\mathrm{DisasterIntensity}_{k,t}$ represents a vector of direct impacts of natural disasters and X'_k is a vector of observed country-year covariates.

The coefficient of interest is β, the estimated relationship between the cumulative intensity of natural disasters to impact a countries population and the population's level of trust at time t

Model 1 is run on a unbalanced panel of 165 country-year observations from 1981-2012, with estimates provided in Table 6. Tables 7 & 8 provides estimates split by OECD status. Note that Huber-White heteroskedasticity robust standard errors are reported for all estimates in this chapter, whilst from Table 7 onwards only the coefficient of interest is reported.

Estimates from the full sample suggest that there are no statistically significant effects of disasters on a country's level of generalised trust. However, splitting our sample into OECD and Non-OECD countries yields a different interpretation. We can see from Table 7 that the disaster intensity coefficients across all models are negative, with model (2) significant at the 5% level. In contrast, Table 8 shows positive and significant coefficients across all models in the sample of Non-OECD countries.

As noted in section 3.2, a Selection on Observables design relies on the untestable unconfoundedness assumption, that is we can confidently state that we observe all covariates that systematically affect selection into treatment. In this context, I would observe all factors that affect the probability of country i experiencing the direct impacts of a natural disaster. Direct impacts are measured using mortality, morbidity and standardised damages, all of which are highly correlated with factors that affect the 'disaster vulnerability' of a country (see section 3.2). Whilst I do condition on most of these factors, my data has limitations, especially as I am unable to control for country-specific geographic characteristics, such has population density, distance to physical triggers or aid flows. Please see section 4.5 for a full description of my data limitations.

For this reason it is possible that the estimated coefficients presented in Tables 6, 7, 8 are biased, probably upwards, leading to incorrect inference. Thus, to account for any missed unobserved heterogeneity I utilise the Selection on Unobservables design described below.

Table 6: Full Sample - Selection on Observables

	Generalised Trust		
	(1)	(2)	(3)
	Killed	Affected	Damaged
Intercept	0.471***	0.477***	0.472***
	(0.112)	(0.111)	(0.113)
log Disaster Intensity	0.002	0.000	0.005
	(0.004)	(0.002)	(0.003)
Education	0.024*	0.024*	0.022
	(0.013)	(0.013)	(0.014)
Income	0.031***	0.030***	0.030***
	(0.010)	(0.010)	(0.010)
Religious dummy	−0.304***	−0.302***	−0.294***
	(0.071)	(0.072)	(0.069)
Ethnic Fractionalisation	0.064	0.065	0.065
	(0.052)	(0.053)	(0.052)
Gastil Index	0.001	0.001	0.001
	(0.007)	(0.007)	(0.006)
Postcommunist dummy	−0.086***	−0.088***	−0.084***
	(0.025)	(0.024)	(0.024)
Gini Coefficient	−0.007***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.001)
Observations	165	165	165
R^2	0.489	0.488	0.494
Adjusted R^2	0.463	0.462	0.467
F Statistic (df = 8; 156)	18.676***	18.620***	19.254***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 7: OECD Sample - Selection on Observables

	Generalised Trust		
	(1)	(2)	(3)
	Killed	Affected	Damaged
log Disaster Intensity	−0.010	−0.009**	−0.005
	(0.007)	(0.004)	(0.005)
Observations	63	63	63
R^2	0.615	0.637	0.609
Adjusted R^2	0.527	0.546	0.522
F Statistic (df = 8; 54)	10.773***	11.836***	10.276***

Table 8: Non-OECD Sample - Selection on Observables

	Generalised Trust		
	(1)	(2)	(3)
	Killed	Affected	Damaged
log Disaster Intensity	0.008*	0.004*	0.012***
	(0.004)	(0.002)	(0.006)
Observations	102	102	102
R^2	0.441	0.439	0.482
Adjusted R^2	0.402	0.400	0.440
F Statistic (df = 8; 93)	9.153***	9.090***	11.367***
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

5.2 SELECTION ON UNOBSERVABLES

To control for any unobserved regional and time heterogeneity I estimate the fixed effects model shown below:

$$(2) \quad trust_{k,t} = \beta DisasterIntensity_{k,t} + \gamma X'_k + \alpha_r + \delta_t + \epsilon_{k,r,t}$$

Supra-national regional fixed effects, α_k, as well as Wave fixed effects, δ_t, are included in model 2 (Nunn & Wantchekon 2011, Aghion et al. 2010). The motivation for including these effects is to capture changes over time that affect countries within a region similarly (Bryan & Jenkins, 2015). Thus, this model is intended to exploit variation in cumulative disaster intensity across countries, conditioned on a vector of covariates that affect disaster vulnerability as well as any unobserved heterogeneity common across supra-national regions and time.

The above fixed effects model is estimated on the pooled sample of the 63 OECD country-year observations (Table 9) and 102 Non-OECD country-year observations (Table 10).

Table 9: OECD Sample - Selection on Unobservables

	Generalised Trust		
	(1)	(2)	(3)
	Killed	Affected	Damaged
log Disaster Intensity	−0.007	−0.008*	−0.003
	(0.008)	(0.005)	(0.004)
Region Fixed Effects	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes
Observations	63	63	63
R^2	0.545	0.569	0.538
Adjusted R^2	0.424	0.443	0.418
F Statistic (df = 13; 49)	4.508***	4.979***	4.386***

The concern under the Selection on Observables design was that I had an omitted variable bias issue, and that inference on these estimates are invalid. However, estimates from Table 9 & 10 yield similar coefficients to those witnessed under the SOO research design,

Table 10: Non-OECD Sample - Selection on Unobservables

	Generalised Trust		
	(1)	(2)	(3)
	Killed	Affected	Damaged
log Disaster Intensity	0.002	0.002	0.012***
	(0.005)	(0.002)	(0.004)
Region Fixed Effects	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes
Observations	102	102	102
R^2	0.540	0.543	0.577
Adjusted R^2	0.450	0.452	0.481
F Statistic (df = 16; 85)	6.249***	6.300***	7.255***
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

providing evidence that this initial model provided a relatively good fit. Once again, we observe that on average the generalised trust of a population in OECD countries fell in proportion to the impact of natural disasters. Moreover, generalised trust tended to rise in proportion to the impact of natural disasters in Non-OECD countries.

5.2.1 *Coefficient Sensitivity Tests*

To estimate the extent of any omitted variable bias in the SOO design I conduct a test from Altonji, Elder and Taber (2000). The Altonji, Elder and Taber (2005) test computes how much greater the influence of unobservable factors needs to be, relative to observable factors, to make the results invalid. [1].

Table 11 shows us values of close to 1 or greater, indicating that the SOO is a valid strategy. The limitation of this sensitivity check is that one has to make the "equal selection" assumption, namely that all unobservables share the same covariance properties as

1 It is based on the ratio of coefficients of regressions including full $\hat{\beta^F}$ or restricted $\hat{\beta^R}$ sets of control variables. The ratio is calculated as $\dfrac{\hat{\beta^F}}{\hat{\beta^R} - \hat{\beta^F}}$

Table 11: Coefficient Stability Test

Sample	*Killed*	*Affected*	*Damage*
OECD	2.33	8.00	1.50
Non-OECD	0.33	1.00	0.9

the observables. Oster (2015) shows that it is necessary to take into account coefficient movements as well as movements in R-squared values to identify omitted variable bias. Thus, in the Oster Test the assumption changes from "equal selection" to "proportional selection", where the covariance relationship is proportional and and relies on a coefficient of proportionality, δ. However, due to programming limitations (Oster Test has not been developed for the R language) I am unable to implement this test, but I make an explicit acknowledgement that is the more robust sensitivity check.

6 METHODOLOGY & ESTIMATES II: REGIONAL ANALYSIS

Chapter 5 was focused on determining the broad cross-country relationship between the cumulative impact of natural disasters impacts and a populations level of trust in a given year. Though useful for framing the broad impacts of natural disasters on a populations trust, it is difficult to draw economically meaningful conclusions, especially across heavily populated and geographically massive countries.

Most disasters, even extremely large ones, tend to only severely affect a concentrated population, with diffuse impacts being felt in the surrounding regions. This chapter provides casual estimates of these concentrated disaster impacts on an affected region's level of trust, by matching survey data with the occurrence of a 'large' natural disaster in a sub-national region.

As noted in section 4.4, for a disaster to be considered 'large' one of the following criteria needed to have been met:

(1) 49 people killed

(2) 65 000 people affected

(3) Standardised Damage value of 6.75

Regions that were affected by a large disaster were marked as 'treated' whilst non-affected regions were marked as 'controls'. The resulting sample consisted of 1973 region-year observations from 1990-2012. Analysis is centred on estimating the causal effect of a large natural disaster on an affected region's level of generalised trust *and* confidence in a vector of first-reponder institutions.

6.1 PROPENSITY SCORE MATCHING - BINARY TREATMENT

I estimate a vector propensity scores ($\hat{p}$), which represents the probability that a sub-national region is selected into treatment, conditional on a vector of observed covariates X'_k. In this case, these observed covariates are the same as used in the previous chapter. These propensity scores form the basis of the matching estimators described below. These matching estimators construct a sample through pairing treated units with control units that have very similar covariate values of X'_k. Under certain assumptions we can claim that the treatment, the occurrence of a large natural disaster, is as 'good as randomly assigned' after conditioning, and thusly allowing causal inference.

6.1.1 *Assumptions*

Conditional Independence The conditional independence or unconfoundedness assumption states that given a set of observable covariates X which are not affected by treatment, potential outcomes are independent of treatment assignment:

$$Y(0), Y(1) \perp D|X, \quad \forall \quad X$$

Caliendo & Kopeinig (2005) note that this implies that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher. Whilst the unconfoundedness assumption is strong, I show in Chapter 5 that the stability of my coefficient of interest under both a SOO and SOU setting provides evidence that the observable covariates X'_k are able to control relatively well for selection into treatment. I assume that this condition holds for the rest of this thesis. Further discussion of the unconfoundedness assumption is presented below when discussing threats to identification in section 6.4.

Common Support/Overlap The common overlap assumption ensures that regions with the same observed covariates X'_k have a positive probability of experiencing a natural disaster (Heckman, LaLonde, & Smith 1999):

$$0 < P(D = 1|X) < 1$$

To best deal with these two assumptions I estimate the propensity score using a flexible logit specification as per Rosenbaum & Rubin (1983). The authors show that if the unconfoundedness assumption holds when conditioning on a vector of observed covariates X'_k, then it is sufficient to condition on $P(X'_k)$:

$$Y(0), Y(1) \perp D|P(X), \quad \forall \quad P(X)$$

The 'curse of dimensionality' is when X'_k is either a high dimensional vector or it is continuous, making it impractical to match treatment and control units and leading to the failure of the overlap assumption. The propensity score matching method has the advantage of dealing with this dimensionality problem by allowing me to use a wider sample of treated and control than if I had used a non-probabilistic matching estimator. Figure 5 presents the density functions of the estimated propensity scores $\hat{p}$ of the control and treatment units.

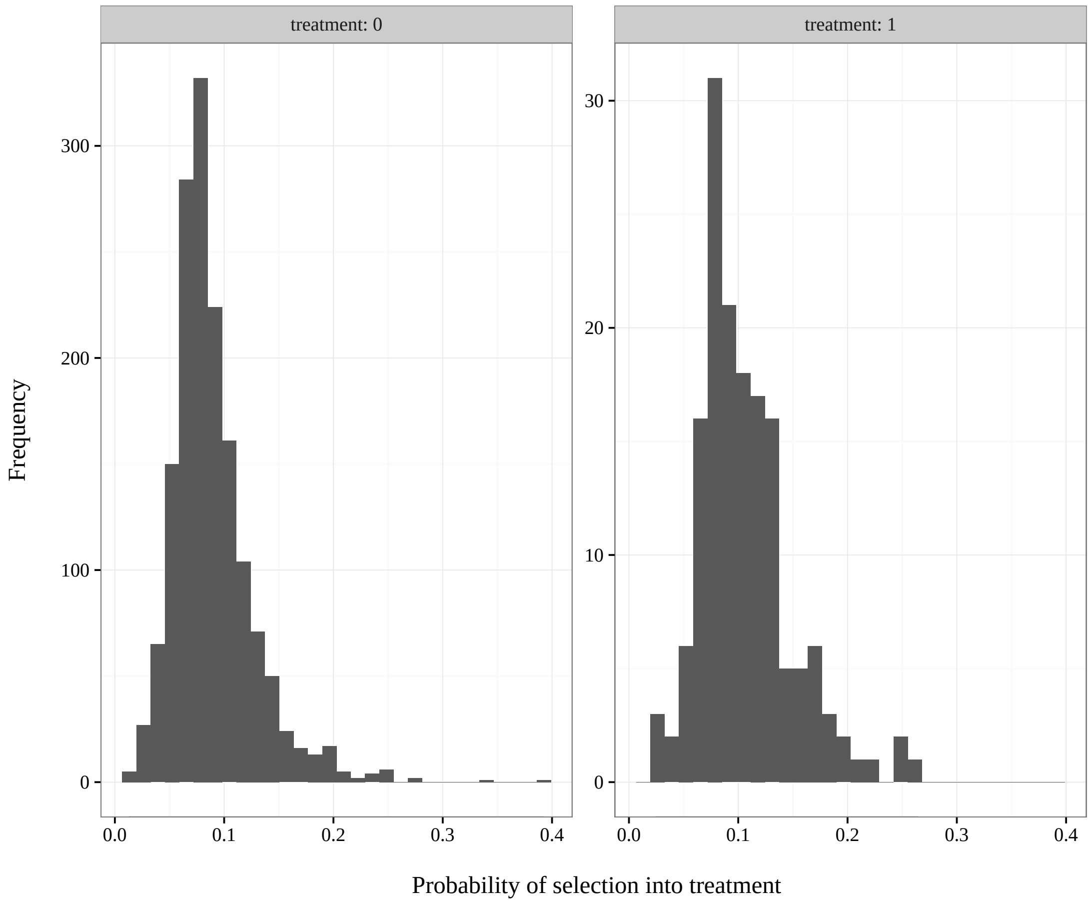

Figure 5: Histogram - Untrimmed Sample

There is considerable similarity in the distribution of $\hat{p}$ amongst both the treatment and control regions, suggesting that the overlap assumption from above holds in this research design. Moreover, to further correct for any remaining imbalances between the control and treatment samples, I weight each region by the inverse of the propensity score, as recommended by Hirano, Imbens & Ridder (2003).

To ensure that the means of the covariates between the treated and control regions are similar, I trim the combined sample to those only with a $\hat{p}$ greater than or equal to 0.07. This limit was chosen so as best to preserve sample size whilst also providing a balance of covariates across treated and control regions. Trimming restricted the sample from

1973 region-year observations to 1476 total observations. Table 12 shows the pre and post-matching balance of covariates from both the untrimmed and trimmed samples. We can see that in the untrimmed sample, five of the covariates (*Sex, Religious, Ethnic Fractionalisation, Gastil Index & Postcommunist*) fail the difference in means test. Following trimming only *Religious & Postcommunist* variables fail the difference in means test, whilst all other covariates exhibit generally closer means between treatment and control regions. All the following analysis takes place on this trimmed sample, with the inclusion of *Religious & Postcommunist* as controls.

Figure 6 plots the histograms of the inversed propensity scores for the treated and control regions after trimming. It is clear that there is still significant overlap between the region types, implying that the common support assumption still holds.

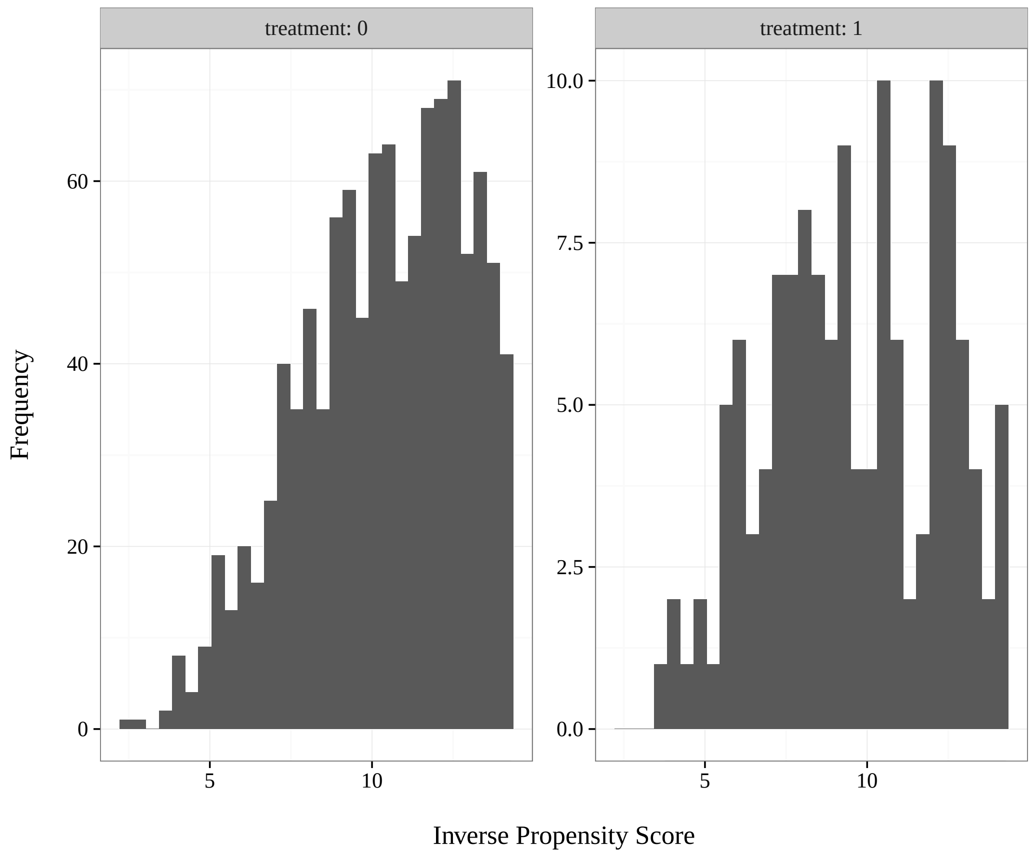

Figure 6: Histogram - Trimmed Sample

Table 12: Balance of Covariates - Untrimmed and Trimmed Samples

	Untrimmed Sample			*Trimmed Sample*		
	Control	Treatment	t-stat	Control	Treatment	t-stat
Sex	0.48	0.50	−4.75*** (0.00)	0.50	0.51	−0.66 (0.50)
Age	41.13	41.58	−0.91 (0.36)	41.65	41.92	−1.03 (0.31)
Education	4.61	4.71	−1.26 (0.21)	4.74	4.75	0.43 (0.67)
Income	4.56	4.70	−0.65 (0.52)	4.73	4.74	0.79 (0.43)
Religious	0.71	0.62	3.42*** (0.00)	0.65	0.61	2.71*** (0.01)
Ethnic Fractionalisation	0.40	0.37	2.41** (0.02)	0.37	0.36	1.81 (0.07)
Gastil Index	3.06	3.12	−2.41** (0.03)	3.04	3.25	−1.94 (0.06)
Postcommunist	0.22	0.05	5.90*** (0.00)	0.23	0.05	5.64*** (0.00)
Gini Coefficient	37.81	37.26	0.94 (0.99)	37.66	37.54	0.54 (0.59)
Observations	1,973	1,973	1,973	1,476	1,476	1,476
Notes:	***Values in brackets under individual t-statistics are the associated p-values ***Significant at the 1 percent level.					

The test conducted is a Welch two sample two-sided t-test, where the null hypothesis is that the difference in means between the two samples is 0. A statistically significant t-test indicates that the difference in means between the treatment and control is different from 0.

6.1.2 *Average Treatment Effects*

Having provided evidence that the methods implemented above allow a sample suitable for causal inference, I proceed to estimate a range of models designed to accurately isolate the true impact of a large natural disaster on an affected populations level of generalised and institutional confidence. As outlined section 4.4 a lagged disaster variable $\mathrm{Disaster}_{k,t-1}$ is used to ensure I measure trust *after* a large disaster. Model (1) specifies a simple linear model on the untrimmed sample conditioned on the vector of covariates X'_k, presented in the Chapter 4. Models (2) & (3) are represented by the following linear equations:

$$(2) \quad \mathrm{trust}_{k,t} = \beta \mathrm{Disaster}_{k,t-1} + \gamma X'_k + \hat{p}_{inv} + \epsilon_{k,t}$$

$$(3) \quad \mathrm{trust}_{k,t} = \beta \mathrm{Disaster}_{k,t-1} + \gamma X'_k + \epsilon_{k,t}$$

where *k* indexes a sub-national measure and *t* is time. Model (2) is conditioned on the vector of covariates, X'_k, as well as the estimated propensity scores $\hat{p}_{inv}$. Model (3) specifies a linear *weighted least squares* equation, with the use of the estimated inverse propensity scores $\hat{p}_{inv}$ as the weights. Both Models (2) and (3) are run on the trimmed sample. Model (3) combines the use of propensity score matching with regression adjustment, reducing any potentially remaining bias and enhancing the estimates. Model (3) is considered 'doubly robust' as if either the propensity score method or regression function is correctly specified, then the estimator is consistent.

The samples used for estimating these models are composed of multiple-countries with units nested at a country level. Thus, I expect that the estimated error term $\epsilon_{k,t}$ to be contain an unobserved country effect u_c. These unobserved country effects arise due to regions within a country having a degree of correlation in their characteristics. Not accounting for these group characteristics would violate the assumption of independently and identically distributed (i.i.d) errors. To account for the presence of unobserved country effects I adjust all standard error estimates for clustering at the country level throughout this chapter. Cluster-adjustment allows observations within a cluster to be correlated, but requires the assumption that observations across clusters be independent (Primo et al., 2007).

Table 13: Average Treatment Effects - Full Sample

	Generalised Trust		
	(1)	(2)	(3)
Disaster_{t-1} *Treatment*	0.022*	0.011	0.019
	(0.013)	(0.014)	(0.015)
Observations	1,714	1,467	1,467
R^2	0.349	0.368	0.335
Adjusted R^2	0.345	0.364	0.331
F Statistic	91.330***	77.123***	73.424***

Table 14: Average Treatment Effects - OECD Sample

	Generalised Trust		
	(1)	(2)	(3)
Disaster_{t-1} *Treatment*	−0.025*	−0.034**	−0.027
	(0.015)	(0.016)	(0.020)
Observations	618	538	538
R^2	0.513	0.515	0.513
Adjusted R^2	0.505	0.505	0.504
F Statistic	63.911***	50.711***	55.527***

Table 15: Average Treatment Effects - Non-OECD Sample

	Generalised Trust		
	(1)	(2)	(3)
Disaster_{t-1} *Treatment*	0.034*	0.030*	0.037**
	(0.018)	(0.016)	(0.019)
Observations	1,096	929	929
R^2	0.334	0.348	0.274
Adjusted R^2	0.328	0.340	0.267
F Statistic	54.357***	44.481***	34.728***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

From Table 13 I observe a positive estimated treatment effect of approximately 2% on the level of generalised trust in an affected population across all model specifications. Splitting the sample into regions in OECD nations and non-OECD nations find contrasting estimates. OECD nations experience between a 2-3% decline in generalised trust (not statistically significant) whilst Non-OECD regions experience between a 3-4% increase in generalised trust in years following a large natural disaster, significant at the 5 and 10 percent level. From Chapter 4, Non-OECD regions on average have generalised trust levels of 23.5%, compared with 33.0% in OECD regions, with similar variances. Thus, a 2-3% decline in trust in OECD regions represents a moderate negative change, whilst a 3-4% increase in trust for Non-OECD populations represents a sizeable positive change.

A hypothesis for these changes in trust could be that OECD populations, with greater average trust levels, have accordingly higher expectations regarding the general trustworthiness of individuals, but the failure to meet these expectations in the aftermath of a large disaster translates into lower levels generalised trust. Conversely, Non-OECD populations have lower expectations regarding the general trustworthiness of individuals, but these low expectations are exceeded in the aftermath of large disasters.

Table 16 presents the treatment effects for an affected population's confidence in a vector of institutions as well civic values. The 'doubly robust' estimates from Tables 14 & 15 are the most conservative, and as such, all remaining estimates throughout Chapter 6 are from this 'doubly robust' specification.

These estimates provide a contrasting picture of the expectations that OECD and Non-OECD populations have in formal institutions during the aftermath of a large natural disaster. From Table 3 in Chapter 4, OECD regions have a mean value of approximately 1.5 in the *Gastil Index*, which is a measure of the existence of political rights and civil liberties (Freedom House, 2012). Non-OECD regions meanwhile have a mean value of 3.9, where lower scores indicate better protection (Gwartney et al. 2015). Moreover, OECD regions have a *Legal Quality* score of 6.8 compared with 5.1 in Non-OECD regions, where higher scores indicate greater qualities. Both these measures have been commonly used in the trust literature as measures of cross-country institutional strength (see Fischer 2010, Bjørkonskov et al. 2010) and indicate that OECD regions on average have stronger institutions than Non-OECD regions.

With this in mind, one hypothesis could be that populations in OECD regions have a much higher expectation that formal institutions will respond effectively during times of

Table 16: Average Treatment Effects, $\mathtt{Disaster}_{t-1}$ *Treatment*

	Full Sample	*OECD Sample*	*Non-OECD Sample*
Civic Values	−0.376	0.322	−0.770
	(0.343)	(0.259)	(0.474)
Confidence - Police	0.014	−0.008	0.032
	(0.023)	(0.015)	(0.026)
Confidence - Army	0.060***	0.056***	0.061***
	(0.017)	(0.026)	(0.021)
Confidence - Church	−0.027	−0.066***	−0.017
	(0.019)	(0.023)	(0.027)
Confidence - Parliament	0.022	−0.077***	0.062**
	(0.020)	(0.018)	(0.03)
Confidence - Civil Services	0.001	−0.017	0.059*
	(0.023)	(0.024)	(0.030)
Notes:	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.		

disaster, whilst Non-OECD populations, with much weaker formal institutions, may not expect as great of a response in the aftermath. Respondents have 'priced-in' these expectations, so a fall in *Institutional Confidence*, like in OECD regions, indicates a failure of formal institutions to meet to meet these higher pre-disaster expectations. In contrast, Non-OECD regions that experience a increase in *Institutional Confidence* indicating a formal institutional response occurred above these lower pre-disaster expectations.

Confidence in law enforcement and displaying civic values showed no significant estimates. The lack of an effect for *Civic Values* was not too surprising, they are aimed to measure the general populations adherence to cooperative social norms, which tend to shift over the long term. Moreover, the potential for significant measurement error in this measure (Knack & Keefer 1997) may impede any treatment effects. On the other hand, the lack of an effect for *Confidence - Police* is surprising. Given that local law enforcement play a role in preparing vulnerable populations as well as assisting in the aftermath, one would expect a treatment effect. One explanation is that the distinction between armed forces and local law enforcement may be blurred during natural disasters, and that the treatment effect on confidence in the *Army* cannibalises some of the effect of confidence in *Police*.

Confidence in the armed forces saw an increase of roughly 6% in years following large natural disasters, a magnitude fairly consistent across both OECD and Non-OECD samples. During times of large disaster it is common to witness armed forces personnel assisting in both the preparation and recovery efforts. Thus, the large positive increases in confidence of *Confidence- Army* are unsurprising. One reason as to the size of magnitude is perhaps that respondents don't often encounter army personnel during civilian life, and their appearance serves as a timely 'reminder' as to their importance in emergency situations.

Treatment effects for confidence in *Church* provide an interesting result, with confidence in religious institutions decreasing by -6.6% in the year *after* a large natural disaster for OECD regions. Section 6.2.1 examines the persistence of changes in trust, and finds that disasters in the *same* year of the survey yields a negligible effect on confidence in *Church* in OECD regions. These findings seem to suggest that affected populations in OECD regions may expect local religious institutions to play a longer-term role in the aftermath of disasters, whilst expecting secular institutions to assist in the short-term recovery efforts. Non-OECD regions, with very high rates of religiosity, see no change in confidence in *Church* following a disaster, perhaps demonstrating the resilience of religious ideas in these regions.

Confidence - Parliament sees a major divergence of treatment effects across OECD (-7.7%) and Non-OECD (+6.2%) populations. The magnitude of this fall in confidence in OECD countries is embodied by the case of New Orleans following Hurricane Katrina in 2005. In this instance there was a lack of action by the parliament in preparing and in responding to Katrina, at least to the level expected by the affected populations. In the case of Katrina, the failure of government to respond in the eyes of the population led to a majority of the blame being placed at the feet of local and federal institutions. The complete opposite may be true in Non-OECD regions, expectations about any potential government response may be much lower and thus when a government institution does intervene they are viewed much more favourably. A similar conclusion can be drawn from the confidence in civil services, institutional responses in Non-OECD regions with lower expectations manifest in more favourable opinions. I provide an in-depth analysis of this mechanism in Chapter 7, with two case studies of large disasters in OECD and Non-OECD settings (Hurricane Katrina & The Indian Ocean Earthquake).

I believe the large magnitudes and significant results estimated for both *Confidence - Parliament* & *Confidence - Civil Services* are further evidence of my initial hypothesis regarding trust and expectations of a formal institutional response. Non-OECD populations have lower expectations regarding the institutional response following a large disaster and thus if any institutional response does materialise, then it as viewed as a 'bonus' relative to expectations. In contrast, OECD populations expect a high level of response from formal institutions and thus any response by formal institutions below the expected level leaves affected populations with the lower levels of confidence in these formal institutions.

6.1.3 *Sampling by Disaster Type*

In sections 6.1.2 & 6.1.4 I have assumed that all treated regions experience a homogenous treatment effect. This is problematic as not all large disasters tend to impact a population in the same way - Floods and Storms tend to affect more people overall whilst Earthquakes are extremely deadly and damaging, but tend to affect a smaller concentration of the population. To account for these nuances, I estimate treatment effects on samples split by disaster type. Disasters are classified into the following types, with the number of treated regions in brackets:

1. *Biological* (Epidemics - 3)
2. *Climatological* (Drought & Extreme Temperature - 16)
3. *Geophysical* (Earthquakes & Landslides - 13)
4. *Hydrological* (Floods - 81)
5. *Meteorological* (Storms - 58)

For each of these treatments new propensity scores were constructed using the matching methods described in 6.1. This is necessary as the baseline covariates that control for selection into each different treatment have changed. For example, the baseline covariates that better predict the likelihood of a large *Geophysical* disaster differ from those that predict *Meteorological* ones.

Table 17 presents the point estimates for the full sample (OECD + Non-OECD), broken down by disaster type. As there were only three region-year observations that experienced *Biological* disasters, they were excluded from the sample. The most striking trend is the consistent positive and significant effects of large *Meterological* disasters on a region. Generalised trust increased by approximately 5% in years following large *Meteorological* disasters, with confidence in institutions increasing on average by approximately 8%. The impacts from *Hydrological* disasters broadly follow those of *Meteorological* disasters, with positive (though smaller) coefficients across most trust variables.

In contrast, *Climatological* provide directly opposite estimates with negative and significant coefficients across most trust variables. One hypothesis becomes evident when one considers the timeline differences between these disaster types. *Hydrological* & *Meteorological* disasters tend to develop, impact and dissipate in a short space of time, whilst *Climatological* disasters tend to develop, impact and dissipate over an extended period of time. The social and institutional response to long-term disasters, such as drought, seem to be falling significantly short of the expected response of affected populations. The same intuition may apply to disasters that kill the most people, large *Geophysical* events. Estimates are generally negative (though insignificant) suggesting that expectations of a social and institutional response are not being met in the aftermath of both *Climatological* & *Geophysical* events when compared with *Hydrological* & *Meteorological* events.

Due to the relatively low number of treatment events, I decline to split the sample by OECD status. This may lead to a regional selection bias, as not all disaster events tend to affect world regions with the same probability. For example, *Meteorological* events tend to be concentrated in the Asian region whilst *Climatological* events tend to take primarily place in Africa. These unaccounted for regional differences may mean comparison is less valid. This limitation could be lessened had there been a larger set of observations for each treatment event.

6.1.4 *Heterogenous Treatment Effects*

To understand how large disasters affect populations with varied economic, social and class characteristics differently, I examine heterogenous treatment effects by interacting covariates with the binary treatment indicator. Table 18 provides the estimates for OECD populations, whilst Table 19 provides estimates for Non-OECD population. One limitation of this analysis is that the bottom two interaction terms of interest, *Disaster*Gini* and *Disaster*Ethnic Frac*, have covariates that vary at the country level, not at a sub-national regional level. Thus, these estimates are not as accurate, allowing only for cross-country inference.

In OECD regions we see that as *Income* and *Education* increase, *Generalised Trust* tends to decrease between 3-4%. This agrees with the hypothesis presented above, the more developed a society, the more it expects to rely on formal institutions during times of disaster.

Table 17: Estimates Broken Down by Disaster Type - Full Sample

	Climatological	*Geophysical*	*Hydrological*	*Meteorological*
Generalised Trust	−0.038	−0.046	0.019	0.053***
	(0.042)	(0.031)	(0.018)	(0.019)
Civic Values	1.539*	0.232	0.003	0.217
	(0.786)	(0.655)	(0.357)	(0.402)
Confidence - Army	−0.093	0.053	0.081***	0.155***
	(0.089)	(0.060)	(0.021)	(0.020)
Confidence - Police	−0.127**	−0.140	−0.014	0.049**
	(0.050)	(0.077)	(0.026)	(0.027)
Confidence - Church	−0.017	−0.010	0.012	0.005**
	(0.004)	(0.005)	(0.020)	(0.022)
Confidence - Parliament	−0.123**	−0.011	0.040	0.092***
	(0.061)	(0.007)	(0.030)	(0.026)
Confidence - Civil Services	−0.075*	0.014	0.041	0.109***
	(0.041)	(0.050)	(0.025)	(0.028)
Notes:	***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.			

The one surprising finding is when *Ethnic Fractionalisation* increases, confidence in *Civil Services* increases. This may be because marginalised communities in OECD regions tend to rely on institutions such as the civil services, especially in times of large disaster.

In a Non-OECD setting we can see that as *Education* increases, *Generalised Trust* correspondingly increases in years after a large natural disaster. In contrast, as the *Gini* coefficient of a country increases, *Generalised Trust* falls. Moreover, countries with greater levels of *Ethnic Fractionalisation* tend to have much lower levels of confidence in the *Parliament* and the *Civil Services*. This set of results are evidence of how populations skewed along social, class or ethnic lines may have different expectations regarding the role trust and institutions play in the aftermath of large disasters.

Table 18: Heterogenous Treatment Effects - OECD Sample

	Generalised Trust	*Army*	*Parliament*	*Civil Services*
*Disaster*Income*	−0.045***	0.078***	−0.018	0.029
	(0.011)	(0.022)	(0.017)	(0.018)
*Disaster*Education*	−0.034***	0.084***	−0.014	0.006
	(0.014)	(0.024)	(0.022)	(0.022)
*Disaster*Gini*	0.005	−0.005	−0.003	0.003
	(0.003)	(0.004)	(0.004)	(0.004)
*Disaster*Ethnic Frac*	0.049	0.019*	−0.001	0.252***
	(0.074)	(0.015)	(0.090)	(0.100)

Table 19: Heterogenous Treatment Effects - Non-OECD Sample

	Generalised Trust	*Army*	*Parliament*	*Civil Services*
*Disaster*Income*	0.023	−0.023	−0.067	−0.059***
	(0.017)	(0.018)	(0.022)	(0.018)
*Disaster*Education*	0.039***	0.008	0.000	0.017
	(0.017)	(0.024)	(0.022)	(0.019)
*Disaster*Gini*	−0.007***	−0.002	−0.000	−0.001
	(0.002)	(0.003)	(0.005)	(0.004)
*Disaster*Ethnic Frac*	0.009	−0.081	−0.276**	−0.204**
	(0.084)	(0.015)	(0.135)	(0.114)

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

6.2.1 *Disasters in Period* t

The sample on which I estimate the treatment effects in sections 6.1.2, 6.1.4 and 6.1.3 matched region-year observations from the WVS at period *t* to a large disaster in period *t-1*. This was done to ensure that I was measuring the impact on trust *after* a large disaster. However, this methodology dictates that levels of trust must still be affected approximately one year later after a large disaster to draw valid conclusions. A priori, it is difficult to know whether this assumption is true or that changes in trust and confidence dissipate shortly after a disaster. Thus, to investigate the temporal nature of trust and confidence, I estimate treatment effects of large disasters that occurred at *t*.

One caveat of this test is that there is no way of knowing how much noise this sample contains (surveys taken after a large disaster are uninformative, but I cannot drop these observations due to a lack of metadata). With this in mind, if the estimated coefficients of interest at time *t* are *significantly* larger than the estimates presented in sections 6.1.2, 6.1.4 and 6.1.3 than this may indicate that changes in the level of trust may dissipate over time. Conversely, if estimated coefficients are *significantly* smaller, this may indicate that the initial change in the level of trust tends to persist over time.

Table 20 presents the results with large disasters in the preceding year, using the 'doubly robust' model specified above. We can see that in OECD regions, there is a negligible negative effect on generalised trust of a large disaster when measured in the same year, but when trust is measured in the following year the magnitude is greater at -2.7%. It should be noted that neither trust measures are statistically significant for OECD regions. I observe a similar persistence effect in Non-OECD regions. The treatment effect of a large disaster on generalised trust in the same year is +3.1% which increases slightly to 3.7% when considering trust in the year after a disaster.

Similar persistence effects are observed when considering the estimates of confidence in institutions presented Table 21. Magnitudes are observed to be approximately the same in both the *t-1* and *t* samples. The most surprising finding is that confidence in the *Church* is negligible in years of large disaster, but highly negative in OECD countries one year after the disaster. One explanation for this may be that affected populations in OECD regions may expect local religious institutions to play a longer-term role in the aftermath of large disasters, and expect secular institutions to assist in immediate short-term recovery efforts.

Table 20: Disasters in period *t*

	Generalised Trust		
	Full Sample	*OECD Sample*	*Non-OECD Sample*
$\mathtt{Disaster}_t$ *Treatment*	0.017	−0.004	0.031*
	(0.012)	(0.015)	(0.019)
Observations	1,191	481	691
R^2	0.327	0.495	0.313
Adjusted R^2	0.327	0.485	0.303
F Statistic	59.283***	47.253***	31.811***

Table 21: Average Treatment Effects, $\mathtt{Disaster}_t$ *Treatment*

	Full Sample	*OECD Sample*	*Non-OECD Sample*
Civic Values	0.077	0.392	−0.079
	(0.263)	(0.322)	(0.357)
Confidence - Army	0.089***	0.095***	0.076***
	(0.015)	(0.026)	(0.021)
Confidence - Police	0.021	0.010	0.044*
	(0.017)	(0.018)	(0.024)
Confidence - Church	0.015	−0.004	−0.007
	(0.015)	(0.021)	(0.019)
Confidence - Parliament	0.053***	−0.067***	0.085***
	(0.020)	(0.018)	(0.003)
Confidence - Civil Services	0.065***	−0.005	0.082***
	(0.017)	(0.021)	(0.023)
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

The t sample consists of 134 region-year observations that are marked as treated. Of these treated regions, 55 region-year observations were also selected as treatment regions in section 6.1.2 (large disasters occurred in both time periods, *t-1* and t). To ensure that the estimates in Table 20 are not being driven by the selection of simply the same regions into treatment, I isolate unique region-year observations that did not have a match with the main sample in section 6.1.2. This leaves 79 unique region-year observations from which to draw results from. Tables 22 and 23 provide estimates of unique region-year observations across the *t-1* and t samples. These estimates represent a comparison between unique regions, which are regions that are not represented in either the *t-1* and t sample. For example, if Sichuan province in China were to experience a large disaster in both of these samples, it is removed entirely to ensure that I am not biasing estimates by selecting the same regions into treatment.

Both Tables 22 and 23 reveal similar levels of changes in trust at different points after a large disaster. For example, Table 22 estimates a positive increase in trust of 7.7% when measured in the same as the large disaster, whilst Table 23 estimates a positive increase of 6.1% in the year *after* large disaster. Given the consistent estimates throughout this section, I can conclude with some degree of certainty that any changes in trust following a large natural disaster seem to persist at least one year into the future. However, as there is potential for inaccurate results when estimating on the t sample, I cannot definitively make any conclusions regarding whether the magnitude of these changes in trust tend to increase or decrease over time.

Table 22: Unique Disasters in period t

	Generalised Trust		
	Full Sample	*OECD Sample*	*Non-OECD Sample*
$\mathrm{Disaster}_t$ *Treatment*	0.049***	−0.010	0.077***
	(0.019)	(0.023)	(0.023)
Observations	839	350	489
R^2	0.385	0.407	0.402
Adjusted R^2	0.377	0.389	0.390
F Statistic	47.094***	23.222***	32.135***

Notes: ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table 23: Unique Disasters in period *t-1*

	Generalised Trust		
	Full Sample	*OECD Sample*	*Non-OECD Sample*
Disaster_{t-1} *Treatment*	0.035^{**}	-0.030	0.061^{***}
	(0.018)	(0.022)	(0.022)
Observations	1193	382	811
R^2	0.380	0.545	0.333
Adjusted R^2	0.375	0.533	0.325
F Statistic	73.255^{***}	45.663^{***}	40.000^{***}
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

6.3 PLACEBO TEST

To test the validity of my findings I run the estimates from section 6.1.2 on a sample where I define a treatment event as a large natural disaster that occurs at time *t*+2. As all the responses were taken at time *t*, one would expect to find no treatment effect when estimated on this placebo sample. The same matching procedure using propensity scores described in section 6.1 was used to trim this placebo sample. Table 24 presents the results of this placebo test after estimating using the 'doubly robust' model specified above.

It is clear from the estimates in Table 24 that a large disaster two years after all responses were recorded has no effect. All point estimates are highly insignificant, providing evidence that the relationships estimated in sections 6.1.2, 6.1.3 & 6.1.4 are not spurious.

6.4 THREATS TO IDENTIFICATION

Omitted Variable Bias - Foreign Aid

As noted above, the SOO hinges on observing all covariates that influence treatment assignment and potential outcomes simultaneously. In the data limitations section 4.5, I noted that EM-DAT fails to provide complete data on aid flows associated with each natural disaster, and as such I am unable to control for aid. There is reason to expect aid flows

Table 24: Placebo Test

	Generalised Trust		
	Full Sample	*OECD Sample*	*Non-OECD Sample*
Placebo Treatment	0.0166	0.013	0.024
	(0.023)	(0.038)	(0.026)
Observations	517	146	371
R^2	0.478	0.456	0.548
Adjusted R^2	0.468	0.418	0.536
F Statistic	47.392***	12.134***	43.793***
Notes:	***Significant at the 1 percent level.		
	**Significant at the 5 percent level.		
	*Significant at the 10 percent level.		

to be correlated with both societal trust and institutional confidence creating a potential omitted variable bias issue, though the direction of this bias is hard to gauge. The aftermath of the Indian Ocean Tsunami brought with it almost US$14 billion in foreign aid. These aid flows were an important factor in the resumption of ethnic conflict in Sri Lanka, which would in turn have affected trust and confidence negatively. In contrast, aid flows into Aceh during reconstruction increased the peace dividend between the government and GAM, the liberation movement. Trust and institutional confidence were reported to have increased following as a result. It is clear that controlling for aid would lead to more accurate estimates than presented above.

7 CASE STUDIES

7.1 2005 HURRICANE KATRINA

In late August 2005, a tropical storm named Katrina emerged over the Bahamas. After briefly making landfall in the south of Florida on August 25, Katrina headed into the warm waters off the Gulf of Mexico. Katrina then began to rapidly deepen, strengthening into a Category 5 hurricane. In the early hours of August 29, 2005, Hurricane Katrina made landfall near the Louisanna-Mississippi state border, as a Category 3 storm. Figure 7 illustrates the path and intensity of Hurricane Katrina.

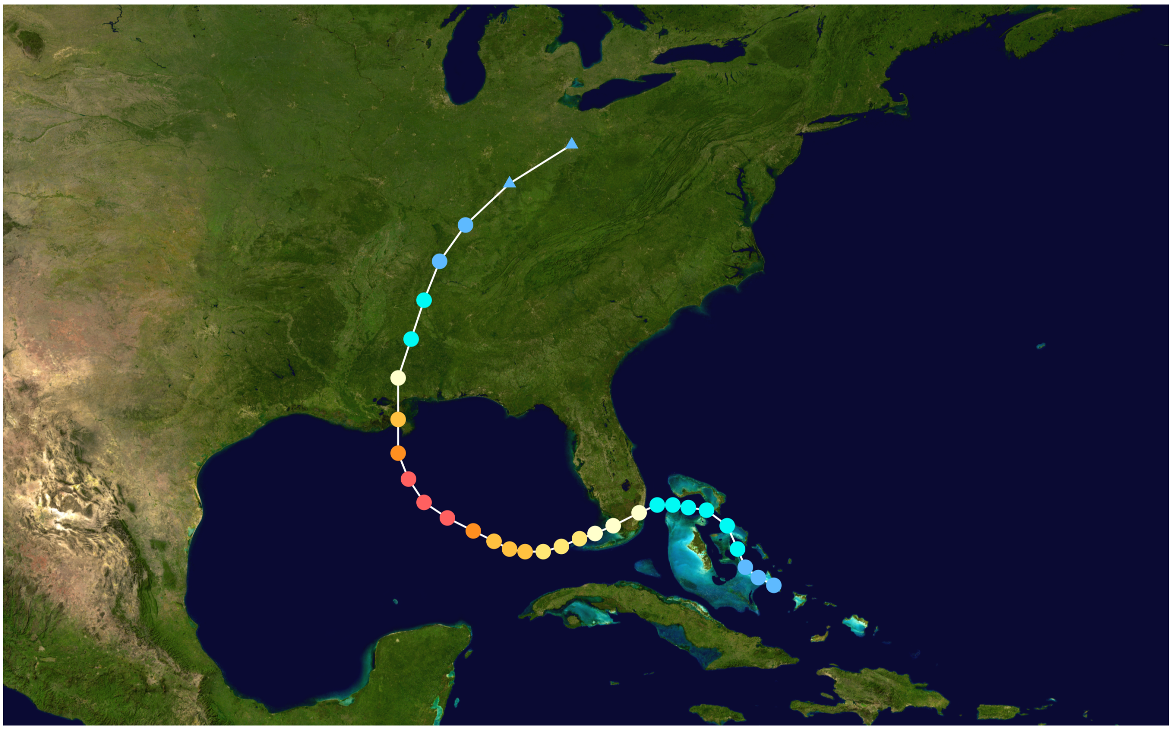

Figure 7: The path of Hurricane Katrina

Though the coasts of Louisiana, Mississippi and Alabama suffered significant damage, it was the city of New Orleans and the surrounding areas that bore the full impact, despite Katrina weakening after landfall. The combination of torrential rain with a strong storm surge breached protective levees, flooding approximately 80% of the city. The destructive flooding of New Orleans culminated in the death of 1,500 residents - two-thirds from drowning, the remaining from exposure, lack of food and water, or preexisting medical conditions (Aldrich, 2012). As a result, the population of New Orleans decreased by over 50%, falling from 484 674 before Katrina (April 2000) to an estimated 230 172 one year later (July 2006) (FEMA, 2011). Moreover, over a million housing units in the Gulf Coast region were damaged, with up to 600 000 households still displaced a month after Katrina. Total damage was placed at US$135 billion, the costliest disaster in U.S. history.

7.1.1 *The Pre-Katrina Institutional Setting in New Orleans*

The Gulf South Region of Louisiana, Mississippi and Alabama has long been on the economic periphery to other parts of the United States, mostly as a result of the development of the US settlement system throughout history (Elliot & Ionescu, 2003). The British Crown's policy of encouraging wealthy Anglicans to the southern colonies, whilst encouraging religious refugees to northern colonies set into motion the development of two distinct socio-economic systems (Elliot & Pais, 2006). The reliance on agriculture in the South, driven by the plentiful supply of cheap slave labour, fed the industrial economies of the Northeast, a division accelerated by the growth of transcontinental railroads. The notion of the South on the periphery began to fade in the late 1960s, when deindustrialisation in the Northeast and Midwest began to push millions toward the metro areas of California, Texas and Florida (Elliot & Pais, 2006). This influx however bypassed the Gulf South, with port cities (such as New Orleans) experiencing little demographic change or economic growth (Glasmeier & Leichencko, 2000).

Contemporary New Orleans, pre-Katrina, carried this legacy of economic futility and social division. In the 1970s, blacks represented half of the city's population, yet held less than five percent of leadership positions (Lewis 2003). The oil shock of the 1980s accelerated the shift of New Orleans as a prominent tourist destination, with on average 13% of residents employed in the low-wage food and accommodations industry, compared with 9% nationwide. However, the loss of added-value industries in the 1980 and 90s resulted in greater unemployment, disinvestment in public schooling and a shift in demographics. In 2005, just before Katrina, two-thirds of New Orleans was black and the city was the sixth-poorest in the US. One in four residents, and four in ten black families lived in poverty (Sherman & Shapiro, 2005), whilst high school drop-out rates were extremely high.

As evidenced in Chapter 6, respondents in OECD regions have higher expectations of an institutional response after disaster. Though New Orleans is in the United States of

America, an OECD country, the social and economic conditions mirrored those of Non-OECD regions, and this suggests that New Orleans was likely to have lower levels of societal trust. These social and economic conditions, pre-Katrina, played a crucial role in determining the interactions with local and federal institutions, as well as the social response in the aftermath.

Flooding Infrastructure & The Diversion of Resources

Though Hurricane Katrina was undoubtedly a disaster of large physical proportions (Category 3 storm), it was actually a physically less intense event than previous storms such as Hurricane Camille (1969) and Hurricane Andrew (1992), both Category 5 storms. Both these previous storms caused only a fraction of the damage inflicted by Katrina, speaking volumes as to the level of unpreparedness of the affected regions, with New Orleans in particular criticised for its lack of adequate flooding infrastructure. Following Hurricane Betsy in 1965, which caused tremendous flooding throughout the city, journalists and academics had long speculated that the New Orleans levee system was inadequate, with Bourne (2004) hauntingly predicting that any major storm or hurricane could produce a storm surge that would lead to 'the worst natural disaster in the history of the US'. This potential threat had been common knowledge, with state and local institutions working on mitigation efforts since the late 1960s. Federal institutions also began taking note, spurred on after six people were killed during flooding following a rainstorm in 1995, with Congress authorising the Southeast Louisiana Urban Flood Control Project (SELA) later that year.

Over the next decade, the Army Corps of Engineers was tasked with carrying out SELA, spending $430 million primarily on shoring up levees and constructing pumping stations (*The Guardian, 2005*). Even with this influx of spending, an estimated $250 million worth of crucial infrastructure projects remained unfinished. In 2003 the Bush administration began significantly diverting resources away from the unfinished SELA and instead toward the Iraq War and homeland security, as well as implementing federal tax cuts (*Times-Picayune, 2004, 2005*). Both the Army Corps and local officials reacted in protest, with the manager of the levee project claiming that only $3.9 million of the $20 million allotted had been provided in 2005 (*New Orelans CityBusiness, 2004*). Moreover, Walter Maestri, emergency management chief of Jefferson Parish, Louisiana stated, "The longer we wait without funding, the more we sink. It appears that the money has been moved in the president's budget to handle homeland security and the war in Iraq...Nobody locally is happy that the levees can't be finished, and we are doing everything we can to make the case this is a security issue for us" (*Times-Picayune, 2004*). This reaction, from a local leader, is evidence that the people of New Orleans were beginning to lose confidence in their formal institutions.

7.1.2 *Institutional Response*

7.1.2.1 *Federal Institutions - FEMA*

In addition to spending cuts on SELA, the Bush administration brought critical changes to the Federal Emergency Management Agency (FEMA), that had significant implications in the aftermath of Katrina. Created in 1979, FEMA initially adopted the 'all-hazards approach', preparing for fires, floods, tornadoes, and nuclear disasters, all situations that required the common methods of rescue, relief and recovery. The election of Reagan in 1980 led to a realignment of FEMAs approach towards the securitisation of the United States, mirroring the increasingly militarised foreign policy of the time. Within four years, FEMAs budget for security-related programs grew to 12 times the allotment for natural disasters (*Slate, 2016*). Following allegations of cronyism and corruption, as well as concern over its disaster preparedness, the National Academy of Public Administration called on FEMA to demilitarise and reembrace the all-hazards approach. The Clinton administration heeded this message, increasing disaster funding and elevating FEMAs director to a Cabinet-level post.

After taking office in early 2001, Bush appointed his former chief of staff as FEMA director, who subsequently oversaw the return of cutting disaster mitigation programs. The events of September 11th, 2001 and the subsequent climate of hyper-securitisation engulfed FEMA, which had lost its Cabinet-level status and was folded into the Department of Homeland Security. Between 9/11 and August 2004, federal grants to FEMA for state and local emergency management decreased from $270 to $180 million, whilst funding for anti-terrorism increased 13-fold to more than $3 billion (*Slate, 2016*). Disaster officials began to milk this new system; to gain funding for flood training officials staged exercises involving a terrorist attack on a dam, whilst researchers filed reports such as 'How Terrorists Might Exploit a Hurricane'. On the ground disaster-funding began to dry up as well, a manager in Alabama reported receiving $250,000 for chemical warfare suits but denied resources to construct an emergency operations centre in tornado-prone counties (*Slate,* *2016*).

The most disturbing story surrounding institutional mismanagement, FEMA and Katrina, centers around an exercise codenamed 'Hurricane Pam'. Fourteen months before Katrina hit New Orleans, 250 officials simulated a hypothetical Category 3 hurricane with massive flooding in the city of New Orleans. Upon observing the massive destruction in their hypothetical experiment, experts began coordinating plans for search and rescue, floodwater removal, short-term shelter and rebuilding for the city of New Orleans. However, due to budget shortfalls and delays, less than 10% of plans, including crucial evacuation and rescue policy, were ever completed. A FEMA spokesman, when quizzed on how many could die if such a storm were to strike, responded, "We would see casualties not seen in the United States in the last century." (*Slate, 2016*). Moreover, a request for search-and-rescue flood training for police, fire and emergency medical personnel in New Orleans was refused "because the curriculum ... did not include a Weapons of Mass Destructions component". It is clear that the rapid change in direction of FEMA and the funding of disaster management in the U.S brought about direct and deadly consequences in both the preparation and aftermath of Katrina. Many of these anecdotes of the unpreparedness and blatant disregard of the welfare of the people of New Orleans only began coming to light in the years following Katrina. They demonstrate a possible mechanism in explaining possible persistence of depressed institutional confidence, not only from those in New Orleans, but all around America.

7.1.2.2 *Local & State Institutions*

The immediate aftermath of Katrina brought feverish reports of civil unrest, with looting, carjacking, murders, thefts and rapes concentrated in New Orleans (*New York Times, BBC, 2005*). This reporting was later determined to be inaccurate, exaggerated and in some cases completely false, leading news agencies to retract these stories (*LA Times, 2005*). To reestablish governance 46 838 federal troops and National Guard were activated and sent to Louisiana, whilst numerous local law enforcement agents were temporarily deputised by the state. Whilst the efforts of the Guard were initially praised, a deeper examination reveals that only 5 804 were active in the disaster zone the day after landfall (*Slate, 2016*). The total number did not reach 10 000, Louisiana's usual number of state guard, till either the third or fourth day of the crisis. By this time, over 45 000 civilians had been trapped in the Superdome and Morial Convention Center, the scenes of the infamous pandemonium and frenzied violence.

The administration's focus with the military campaign coupled with the expectation of massive civilian 'insurgents' (which never materialised) resulted in the tendency to approach Katrina operations as an extension of the US wars abroad. The military media encapsulated these warlike sensibilities, with the *Army Times* headline on September 3rd declaring, "Troops begin Combat Operations in New Orleans", and the commander of the Louisiana National Guard's Joint Task Force stating, "We're going to go out and take the city back." The troops were tasked with both reestablishing control and rescue, but subsequent reports emerged of troops aggressively approaching flood victims as adversaries, and forcing evacuations even after floodwaters began receding (*Slate, 2016*).

There were several allegations of police misconduct, with several shootings between police and unarmed New Orleans residents. There were also reports of police abusing their power and engaging in civil unrest themselves, in one case the New Orleans Police Department stripping a Cadillac dealership of its vehicles, only for some of them later to be found sold in Texas. These actions led to "New Orleans being like a police state", where citizens were sometimes arrested in their own houses for looting.

The uncertainty surrounding the state of martial law in New Orleans post-Katrina played a crucial role in explaining the actions of local law enforcement. After hearing that a police officer had been shot during a pat-down search of some suspects, Mayor Ray Nagin off-handedly stated in a local radio interview that, "We need to declare martial law". Opportunistic local leaders and media news outlets echoed this sentiment, with the Jefferson Parish president impetuously declaring that his district was "under martial law, and there's only marshal: me". Louisiana's governor, Kathleen Blanco further heightened tensions during her now infamous "shoot-to-kill" speech, "I have one message for these hoodlums: these troops know how to shoot and kill, and they are more than willing to do so if necessary, and I expect they will" (*The Guardian, 2009*). Some law enforcement took these comments literally, with police leaders such as First District Captain James Scott, instructing officers that, "We have authority by martial law to shoot looters".

The residents of New Orleans, living in an OECD nation with stronger institutions, had high expectations of an effective response by both federal and local institutions in the aftermath of Hurricane Katrina. It is abundantly clear that three of the most prominent firstresponder institutions, the Parliament/Government, Army and Law Enforcement failed the people of New Orleans.

7.1.3 *Social Response - The Lack of Generalised Trust*

Studies in the aftermath of the hurricane revealed that several pockets of New Orleans had rebounded to almost the same population, economic and cultural levels as pre-Katrina, despite widespread damage to the majority of the city (Weil 2010). Aldrich (2012) points to two neighbouring suburbs that suffered similar damage, the Lower Ninth Ward and Village de L'Est, as evidence. Five years on and despite having comparable levels of poverty, the Lower Ninth Ward had recovered only one-fourth of its pre-Katrina population whilst Village de L'Est experienced a 90% population recovery, with business reopening within two years of the disaster (Aldrich, 2012). In Village de L'Est, a predominately Vietnamese neighbourhood, local activists worked to maintain social networks both during the evacuation and in the aftermath. Community leaders, such as Father Vien Ngyuen, drove to evacuation shelters in Texas, Arkansas, and Louisiana to meet with citizens of New Orleans who had left the city, with Father Vien taking photographs "of every member of the community he met to confirm their safety to friends and families in distant cities" (Chamlee-Whright 2010, p. 62). Moreover leaders of Village de L'Est set up Vietnamese-language radio channels in cities with evacuees to broadcast plans for rebuilding (Aldrich, 2012).

In October 2005, when residents were allowed back into New Orleans, the residents of Village de L'Est did so en masse. Local religious and community organisations supplied necessities, whilst when fiver hundred signatures were needed to prompt utility companies to restore power, over a thousand residents signed on the first day (Aldrich, 2012). The case of Village de L'Est illustrates how an affected population use social capital trust as an informal insurance mechanism, overcoming collective action problems to enable a more efficient and coordinated recovery.

In contrast, the neighbouring suburb of the Lower Ninth Ward, underscores how a lack of social trust translated into an absence of informal assistance when formal institutions failed. In a survey, residents of the Lower Ninth spoke of the disconnect that existed between the civil society and decision makers, whilst a past president of the Lower Ninth Ward Neighbourhood Association noted, "My area has not traditionally been open to connecting with other groups of people due to the fact that we felt we did not need to work with others" (Aldrich, 2012).

These two neighbourhoods paint a contrasting picture of an organised neighbourhood mobilising and overcoming collective action problems, whilst fragmentation in the other stymied recovery efforts. Though residents of resilient suburbs, such as Village de L'Est, were able to recover quickly and improve quality of life, their collective actions actually had a role in increasing society-wide inequality following Hurricane Katrina.

Post Katrina, with more than a million evacuees dispersed and 434 000 homes destroyed, local and federal institutions stressed constructing temporary housing, such as trailer parks, as their number one priority. Trailer parks are examples of public bads, which are projects that impose focused costs on local communities but tend to provide diffuse benefits to cities as a whole (Kelly et al. 2005). Half of the 64 parishes across Louisiana banned new trailer sites following Katrina. In the Algiers parish of New Orleans, local residents blocked construction and survey equipment, whilst Davis & Bali (2008) estimate that one in four proposed FEMA trailer parks that were initially accepted were later rejected by host communities. Aldrich (2012) finds that zip codes with stronger levels of trust and social capital were able to mobilise and block trailer development, with these suburbs on average receiving fewer than 100 trailers, whilst less active neighbourhoods, such as the Lower Ninth, received on average 1200 trailers. This "not in my neighbourhood thinking" as described by Mayor Ray Nagin, demonstrate how disaster in a fragmented society with low levels of generalised trust can further deepen existing class, race and ethnic inequalities.

The souring relations between society and those institutions charged with the recovery hastened into effect a general sense of chaos amongst the civilian population. It was now that a lack of generalised trust amongst the population began to reveal itself. The clear racial and class fault lines on which New Orleans had been built on began to rear its ugly head. One such example was the spate of 'vigilante justice', where suburban white men from outside New Orleans collected arms and systematically murdered several black men, whilst injuring and threatening others (Thompson, 2009).

7.1.4 *Long Term Effects - Migration & Mental Health*

The joint failure of institutions and the general society to accomodate displaced citizens acted as a trigger for large outmigration from the Gulf Coast region. Specifically, Myers et al. (2008) show that places which once housed marginalised populations were the most likely to migrate away following Katrina, corroborating with media accounts of a disproportionate displacement of low-income African American residents (Frey & Singer 2006). True (2016) lends further evidence, noting that there was a negligible difference in women as a percentage of the population pre- and post-Katrina (54% vs 52%) but that black women as percentage of the female population declined significantly from 47.2% to 37.3%, again emphasising that disasters hit minority groups the hardest. Hurricane Katrina prompted one of the largest migration events in the history of the US, with the displaced registered in all 50 states. The scale of this migration demonstrated the far reaching impact that Katrina had not just on the city of New Orleans, but on the United States as a whole.

As noted above, neighbourhoods with denser social networks were able to overcome barriers to collective action and mobilise as a group to stop the construction of temporary housing projects in their area. Studies subsequently found significant disparity between black and white communities in New Orleans in the number of FEMA trailers constructed (Craemer 2010). Moreover, Fussel & Lowe (2014) demonstrate how relocation and unstable housing post-Katrina led to low-income black communities burdened with greater mental health problems more than 3 years after. Low-income female survivors also reported lower levels of social support, whilst front-line recovery workers - predominately women and people of colour - faced greater health risks (Lowe & Willis, 2015; Weber et al., 2012). The civil unrest, migration and mental health problems in the wake of Hurricane Katrina fell disproportionately on those residents in low-trust, fragmented neighbourhoods, further entrenching social and economic norms that drive inequality.

Moreover, they show how an exogenous event, like a natural disaster, can lead to changes in attitudes (in this case large falls in trust) which may persist well into the future. This case study corroborates with the evidence presented in Chapter 6, that OECD regions on average experience falls in both societal trust and institutional confidence that persist in time, although the magnitude of these falls in New Orleans was much greater.

7.2 2004 indian ocean earthquake & tsunami

In the early morning of 26 December 2004, two massive underwater earthquakes approximately 240 kilometres off the west coast of Sumatra, ruptured the ocean floor. Within eight minutes the fracture had released 23 000 times more energy than 'Fat Man', the atomic bomb that destroyed Nagasaki. Segments along the fault surged upwards by tens of metres, lifting the whole column of water above, and generating tsunami waves as high 30 metres when it hit the coasts of Indonesia, Sri Lanka, India, Thailand and Myanmar (Sheth et al., 2006). The Indonesian city of Banda Aceh was the hardest hit, with over 60 000 or approximately one-quarter of its total population killed. In total, 227 898 people perished, with nearly 170 000 in Indonesia, and 51 000 in the coastal areas of Sri Lanka and India, whilst estimated cost of the damage amounted to US$10 billion (*BBC, 2014*). This devastation prompted a worldwide humanitarian response, with more than US$14 billion in foreign aid contributed.

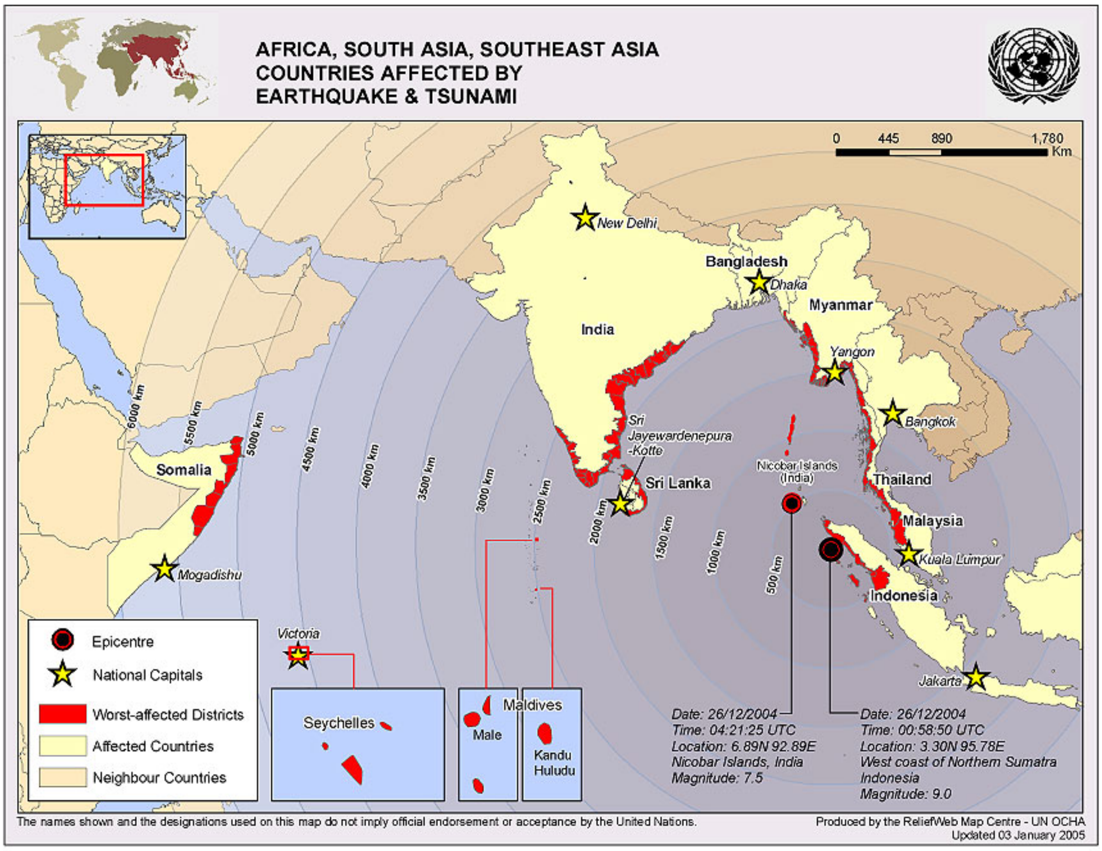

Figure 8: Affected Areas of Earthquake & Tsunami

7.2.1 *Tamil Nadu*

The coastal hamlets of Indonesia, India, Sri Lanka and Thailand devastated by the tsunami bounced back at extremely different rates. This section focuses on the recovery of small groups of fishing villages in Tamil Nadu, a state in the southeast of India. Approximately 8 000 people were killed in the thirteen coastal districts of Tamil Nadu, whilst surveys in the aftermath of the tsunami showed that more than three in five families perceived that they had at least lost a quarter of their income (Rural Education and Development Society; Fritz Institute 2005). More than 150 000 homes were destroyed along with important infrastructure, such as roads, bridges and ports, with total damage placed at US$1.3 billion (World Bank 2006).

This section presents the case of how some villages, with organised social groups were able to mobilise and overcome collective action problems which ultimately sped up the recovery process, whilst other villages lacking in strong networks were not able to rebound with the speed or to the same level as their neighbours. However, villages with these stronger social networks tended to exclude any non-members and minorities, exacerbating any class and ethnic differences that existed pre-disaster.

7.2.1.1 *Uur Panchayats and Parish Councils*

In many fishing villages in coastal Tamil Nadu, non-state organisations made up of same-caste fisherman dominate the social order (Gill 2007). The *Uur Panchayats* are formed by Pattinavars in the southeast, whilst *Parish Councils* are formed by Catholics in the south. Bavinck (2008) points out that many villages are homogenous, with Pattinavars families making up ninety percent of the population, with Dalits forming the rest. Both the *Uur Panchayats* and *Parish Councils* serve a number of functions in these villages, they enforce informal laws and norms as well as pooling and distributing resources (Ostrom 1990). Members who marry outside their castes may be ostracised and their families fined. Moreover, during the monsoon when fishing catches are low, these groups manage and distribute supplies to members, demonstrating their collective coordination (Bavinck 2008).

Following the 2004 tsunami, these groups took on increased importance, serving as conduits for aid distribution from both the government and NGOs. Government officials report finding representatives of these groups with lists of the deceased and wounded as well as specific requests for materials, food and supplies (Aldrich 2008). The *Uuur Pan-*

chayats and *Parish Councils* would then store all resources and then distribute them equally amongst their members (Aldrich 2008). The Tata Institute (2005) provides an example, when in one village an *Uur Panchayat* collected all the boats pledged by the NGOs, before selling them to those who could buy them and then distributing this revenue amongst its members.

Aldrich (2008) examines villages that lacked *Uuur Panchayats* and *Parish Councils* and finds that they had a rougher path to recovery, with housing, infrastructure and aid receipts all much lower than villages that had these groups. These isolated villages were unable to connect with government or NGOs and as such had to rely solely on the, "ingenuity of women, mutual support within extended families, and minimal income derived from intermittent, informal sector jobs" (Bunch et al., 2005, p. 3). Villages that lacked either organised groups or where there was general distrust amongst individuals, usually as a result of significant ethnic heterogeneity, exhibited even poorer recovery outcomes, a finding consistent with Chapter 6. Salagrama (2006, p. 60) describes how the lack of coordinating mechanisms as well as social fractures "precluded their coming together for collective and effective articulation of their views". Residents that were a part of these villages lacking in social institutions and trust recognised that their recovery had been compromised, "We are planning to make a panchayat ... I believe that people with panchayats received more benefits because they were better organised" (Aldrich 2008, p. 101). These anecdotes provide evidence of the role that local institutions can play in the aftermath of large disaster, whilst also highlighting how a general distrust can hold back a society on their path to recovery.

7.2.1.2 *Systematic Discrimination*

The strong social networks facilitated by organisations such as the *Uur Panchayats* and *Parish Councils* meant that members in these villages were better able to mobilise, overcome barriers to collective action and speed up the recovery process. However, these benefits tended to only extend to members of these organisations, leaving traditionally marginalised groups, such as Dalits, women and the elderly excluded from the recovery process. Louis (2005) finds in a survey of sixty tsunami-affected villages that approximately 7 800 people belonging to marginalised groups were deemed eligible for relief but failed to receive any, primarily because of systematic discrimination by the *Uur Panchayats* and *Parish Councils*. One instance of this overt exclusion was when a local family, who upon failing to receive housing, approached the local institutions for help only to be told that they were from the wrong caste, and hence didn't 'qualify' for aid (Chandrasekhar 2010).

In other cases, Dalit families were forced out of temporary shelters or beaten when they stood in line to receive assistance (Gill 2007; Tata Institute 2007). Aldrich (2008, p. 100) relays the thoughts of villagers, "In the South, if you are not in the church, you are not on the disaster rolls".

There has been much research (Nakagawa and Shaw 2004, Aldrich 2008) that demonstrates how strong local institutions contributed to a community's disaster resilience, through serving as focal points for external aid bodies and providing strong social support structures, overall leading to fast rates of recovery for members. Villages with no organised local institutions and/or weak social ties, perhaps due to increased caste and ethnic heterogeneity, were only able to gather one-third the financial assistance, and in general experienced far slower rates of recovery. Whilst villages with strong local institutions were able to recover at quicker rates, these benefits were only extended to members, exacerbating any inherent caste and gender imbalances. This systematic discrimination was far less evident in villages without *Uur Panchayats* and *Parish Councils*.

7.2.2 *Sri Lanka*

Around 2 hours after the eruption of the earthquake, tsunami waves reached Kilinochchi in the east of Sri Lanka. Over the next fifteen minutes the 2 260 kilometres east and north were hit with waves up to 10 metres high. In the Mullativu area the waves failed to break and instead continued 5 kilometres inland as a fast moving tidal bloc. The final death toll stood at over 37 000 with over one and a half million left displaced.

7.2.2.1 *Local Organisations*

Similar to the *Uur Panchayats* and *Parish Councils* in Tamil Nadu, some villages in Sri Lanka relied on community-based organisations in the aftermath of the tsunami. These local organisations can be broadly split into fishery cooperatives, women's societies, rural development societies and community-based NGOs. Minamoto (2008) finds evidence that tsunami victims harboured expectations that the only source of assistance would be from these local organisations during recovery, and had very low expectations of any formal institutional response materialising. When aid and assistance from formal institutions did begin to arrive, it was channelled through these local organisations.

There tended to be asymmetric recovery rates across these four organisations, with members of rural development societies feeling strongly that prior networks with formal organisations played a large role in the recovery process. Members of rural development societies reported that links to formal institutions were strengthened during the reconstruction, and indicated that they had higher levels of confidence in local and formal institutions almost four years on. This is evidence of how both societal trust and institutional confidence can increase in the aftermath of disasters, in this case the local organisations playing an important role in linking victims to formal institutions.

Whilst members of rural development societies experienced positive increases in trust and institutional confidence, tsunami victims that were members of local NGOs had an altogether different experience. Minamoto (2008) reports that many NGOs were formed after the tsunami and as such, had no prior connections to formal institutions. These NGOs tended to receive comparatively less assistance, with members also experiencing frustration they were being 'forced to participate' in these less fruitful programs. Similar to case in Tamil Nadu, Minamoto (2010) finds that victims who were members of some local organisation still had higher rates of recovery and in general higher trust and confidence, even four years after the tsunami, a finding again supported by the persistence of increases in trust and confidence presented in Chapter 6.

7.2.2.2 *Conflict*

The villages hardest by the tsunami were also areas that had been engulfed by the ethnic conflict between the Liberation Tigers of Tamil Eelam (LTTE) and the Sri Lankan military. Despite grave concerns from international observers that either side would exploit the disaster situation, there was reported to be a high level of assistance across ethnic lines during the humanitarian efforts immediately following the tsunami. However, as reconstruction began, foreign aid to the value of US$650 million began pouring in. The LTTE increased hostilities in response and started denying NGOs access to the affected regions in the North and East provinces. Instead they ordered all relief agencies to channel aid through it's own body, the Tamils Rehabilitation Organisation (Beardsley & McQuinn, 2009). There were also claims that the LTTE recruited child soldiers from refugee camps (UTHR 2005). Shortly after the ethnic conflict resumed in full force, with 2 500 killed and 200 000 displaced in 2006 (ICG 2006).

The resumption of conflict in Sri Lanka contrasts the case of peace between the Indonesian government and the Free Aceh Movement (GAM). Prior to the 2004 earthquake and tsunami, prospects of peace had worsened, with short-lived ceasefires common and intense armed violence common (Beardsley & McQuinn, 2009). Following the tsunami, Aceh was the worst affected region in Indonesia, with an estimated death toll of 164 000 people (Pandya 2006). This devastation brought with it a massive influx of foreign aid, totalling approximately US$5 billion. In stark contrast to the LTTE, GAM welcomed aid workers whilst using the large media contingent to place the Acehnese on the radar of the international community. Beardsley & McQuinn (2009) argue that these two factors, aid and exposure, increased the peace dividend of an agreement. Most international observers give the Indonesian government much of the credit for the peace deal, one report stating that "The Indonesian government ... used the tsunami to build trust with the Acehnese and to begin a peace process" (*Overseas Development Institute, The Guardian, 2005*).

These contrasting cases reveal two very different outcomes; the effective disaster response of the Indonesian government lead to an increase in institutional confidence which then facilitated successful peace negotiations. It is clear to see how this increase in trust and confidence could persist over time. As demonstrated above, the Sri Lankan victims tended to rely on local organisations as opposed to the formal institutions, at least when compared to the Acehnese. Though increases in institutional confidence were reported, the government failed in brokering peace and a resumption of conflict ensued. As well as being informative of the mechanisms behind the changes in societal trust and institutional confidence, these cases also demonstrate how the influx of foreign aid can add further complexity to the study of natural disasters. These cases provide further evidence of the need to control for aid set out in section 6.4.

8 DISCUSSION

8.1 FINDINGS

Chapters 5 & 6 presented empirical evidence of the differing relationships between trust and large natural disasters across OECD and Non-OECD settings. Moreover, heterogenous treatment effects as well as impacts of different disasters on trust were estimated. Finally, the persistence of these changes in trust were examined. Chapter 7 built on these findings through documenting the cases of New Orleans after Hurricane Katrina and local villages following the Indian Ocean Earthquake and Tsunami. These findings are discussed in the sections below, with a particular focus on the external validity as well as policy implications in the context of accelerating climate change.

The empirical work in Chapters 5 & 6 found strong divergences between OECD and Non-OECD population's change in trust following a large natural disaster. Whilst OECD regions on average experience falls in both generalised trust and institutional confidence, Non-OECD regions on average experience a sizeable increase. One explanation is to do with the initial expectations of a population; OECD populations, with higher levels of generalised trust and stronger institutions, have higher expectations of the trustworthiness of individuals and institutions prior to a disaster whilst Non-OECD populations, with lower levels of generalised trust and weaker institutions, have lower expectations. Interestingly, these changes in levels of trust were found to persist one year after a large disaster, indicating that there are some long-lasting shifts in confidence in affected societies.

The case studies set out in Chapter 7 provided further evidence of the disaster impacts presented in Chapter 6, whilst also detailing the mechanisms that drive these changes in trust and confidence. The case of Katrina saw the people of New Orleans lose confidence in institutions in the aftermath following gross mismanagement by the federal government and outright corruption and brutality by local law enforcement. Episodes of racial violence and the refusal to accomodate displaced citizens indicated high levels of distrust amongst the general population. Moreover, these falls in both institutional confidence and societal trust were shown to persist years into the future, catalysed by media reports of the diversion of disaster mitigation resources and the entrenchment of marginalised communities.

The case of the 2004 Indian Ocean Tsunami shows how some villages with higher levels of trust, facilitated by local organisations, were able to facilitate a quicker recovery by overcoming collective action problems faced in low-trust villages. These high-trust villages were able to reach out to formal institutions and gain more than three times the amount of assistance received by low-trust villages, which were built on social fractures that precluded them to mobilise and rally for aid. In Sri Lanka, there was strong evidence that increases in trust and institutional confidence persisted more than four years following the tsunami, which along with Katrina, is perhaps an indication that changes of attitudes following disasters persists for even longer than what was presented in Chapter 6.

The negotiation of peace in Indonesia was built on the back of an increase in institutional confidence following the tsunami response, contrasting the resumption of ethnic conflict in Sri Lanka. Both these peace processes had in common large influxes of foreign aid, resources that played a pivotal role in influencing the incentives of the warring parties and ultimately in the chances of peace. It is clear that one should control for aid when analysing natural disaster impacts, something I fail to do as data was unavailable to me. As is evident from the divergent outcomes of the Sri Lanka and Indonesia conflict, the direction of any bias due to the omission of aid flows are hard to predict.

Analysing different types of natural disasters adds another layer of complexity to the discussion, especially when considering how climate change will change the intensity and frequency of some types. After controlling for selection into treatment, I find that *Meteorological* & *Hydrological* disasters on average have a negligible to moderately positive impact on the change in generalised trust and institutional confidence. In contrast, *Climatological* & *Geophysical* disasters are associated with moderately negative changes in trust and confidence. These divergences in findings are evidence that they type of disaster influences how populations form their expectations of social and institutional responses. An extension of this notion can be found when analysing the heterogenous treatment effects following a large natural disaster. Economic, class and ethnic characteristics were found as significant influencers as to how a population forms their expectations of social and institutional responses.

8.1.1 *External Validity*

A major advantage of conducting cross-country studies is that estimates are drawn from a wide range of observations, potentially allowing for easier justification in generalising results. To further justify this notion, I present a simple balance of covariate means across both OECD and Non-OECD countries (Table 25). The heading *Internal* refers to the sample used for estimating the results presented in Chapter 6, whilst *External* refers to the full sample of the WVS.

As is evident, most of figures are extremely similar across the *Internal* and *External* samples for both OECD and Non-OECD countries. The only slight concern is the *Gini Coefficient* is higher in the *External* sample than what was used to estimate the results. Despite this very minor difference in means between the *Internal* and *External* sample, I strongly suspect that the findings discussed in section 8.1 are able to be generalised to regions not included in the internal sample. The strong evidence for external validity is encouraging when considering general policy prescriptions that may arise from this research.

8.2 climate change and natural disasters

This section aims to contextualise the findings presented in section 8.1, as well as framing the discussion around the policy implications set out in section 8.3 below. There is strong scientific consensus that human activity is unequivocally warming the climate, and that since the 1950s many of the observed changes are unprecedented (IPCC, 2013). These changes include warming of the atmosphere and ocean, diminishing snow and ice, sea level rises and increased concentrations of greenhouse gases. By 2035, the global mean surface temperature (atmospheric temperatures) are likely to increase by between 0.3°C and 0.7°C, whilst by 2100 these ranges increase to 1.8°C and 4°C. Abatzoglu & Williams (2016) find recent evidence linking increases in atmospheric temperatures have substantially amplified the chronic risk of forest fires across the western continental United States. Moreover, there is high confidence that normal weather cycles, such as the El Niño Southern Oscillation will intensify, bringing about more frequent and extreme droughts.

Sea levels will rise, with conservative estimates predicting increases between 0.26 and 0.82 metres by 2100 (IPCC, 2013). Moreover, normal precipitation events will increase in du-

Table 25: Balance of Covariates - External Validity

Sample	*OECD*		*Non-OECD*	
	Internal	External	Internal	External
Sex	0.49	0.48	0.50	0.49
Age	44.54	43.95	39.06	38.96
Education	4.76	4.86	4.58	4.67
Income	4.65	4.71	4.53	4.54
Religious	0.58	0.59	0.74	0.76
Ethnic Fractionalisation	0.29	0.27	0.43	0.46
Gastil Index	1.51	1.47	4.09	3.89
Postcommunist	0.19	0.20	0.21	0.23
Gini Coefficient	35.84	36.19	39.72	41.03

Notes: Values reported are the means of each sample

ration and intensity, with extreme weather events, such as landfalling typhoons increasing in frequency and extremity. Mei & Xie (2016) predict that enhanced ocean surface warming will lead to further intensification of typhoons around the densely populated regions of eastern China, Taiwan, Korea and Japan. Increases in ocean acidity has lead to widespread destruction of coral reef, natural systems that usually protect coastal areas from storm surges (Cavallo & Noy, 2011).

Whilst there is clear evidence that climate change will lead to the intensification and frequency of *Hydrological*, *Meteorological* and *Climatological* events, there is no current link between climate change and *Geophysical* events. However, as was the case in the 2004 Indian Ocean Earthquake and the 2011 Tohoku Earthquake, large *Geophysical* events can be accompanied by massive tsunamis and floods. These events would be expected to increase in intensity due to climate change.

8.3 policy implications

Through analysing the structural determinants of the costs incurred from natural disasters researchers have shifted the thinking away from natural disasters being purely an exogenous event. This shift in thinking has subsequently allowed for concentrated policy action in areas that contribute to this vulnerability (Cavallo & Noy, 2011). Perrow (2007) argues that policy should focus on mitigation efforts, primarily working to 'shrink' the targets vulnerable to catastrophic disaster through lowering the concentration of people, utilities and infrastructure in disaster-prone locations. Current policy prescriptions revolve around *ex ante* insurance and *ex post* assistance. Similar to the moral hazard problem in insurance markets, *ex post* assistance generates a "Samaritan's dilemma, ie. an increase in risk taking and a reluctance to purchase insurance when taking into account the help that is *likely* to be provided" in the aftermath of large disasters (Cavallo & Noy, 2011, pp. 89). The findings presented in section 8.1 above are useful in that they advance the knowledge of how different populations form these expectations of *ex post* assistance.

For example, OECD regions on average have higher expectations regarding the social and institutional response (*ex post* assistance) following a large disaster, and show depressed levels of confidence and trust if these expectations are not met. To avoid these falls in trust, which have negative impacts on the efficiency of markets and institutions, policymakers could either promote *ex ante* insurance to a greater extent (which may alter expectations) or to increase levels of *ex post* assistance. On the other hand, increasing levels of either *ex ante* insurance and/or *ex post* assistance may lead to even greater gains in societal trust and institutional confidence in Non-OECD populations. Section 2.2 outlines the importance of generalised trust in an economy, the broad benefits revolving around more efficient functioning of markets and institutions (Coleman, 1990; Putnam, 1993; La Porta et al., 1997; Easterly et al., 2006).

These findings provide clarity on the expected role of institutions in both the immediate aftermath and in the long-term rebuild following a natural disaster. For example, in the short-term I find that OECD population's trust in formal institutions falls significantly in the immediate aftermath of a large disaster, and that these changes in trust persist at least one year later. In contrast, that confidence in religious institutions remains stable in the immediate aftermath of large disaster, but turns highly negative one year *after* a disaster. This is evidence that OECD populations place higher expectations on secular institutions

(*Parliament, Civil Services, Law Enforcement*) in short-term recovery efforts, but expect local religious institutions to play a role in the long-term recovery of a devastated area. These insights into the expectations of a society should provide a degree of clarity as to the expectations of an institution in the aftermath of large disaster, and the subsequent appropriate policy response.

This discussion also provides evidence of differing expectations with respect to different types of disaster events, with *Climatological* & *Geophysical* disasters on average associated with negative changes in trust. Policy regarding *ex ante* insurance and *ex post* assistance should therefore be malleable to these different types of disasters. To avoid these falls in trust and confidence, policymakers could ensure that respondents exposed to longer-term droughts receive adequate *ex post* assistance, or through promoting *ex ante* insurance to regions at-risk of large earthquakes.

Moreover, the unique economic, class and ethnic composition of a society were found to alter how a population form their expectations of societal and institutional responses following disaster. For example, Non-OECD societies with increased inequality and greater ethnic fractionalisation were found to have exhibit negative changes in trust and confidence in institutions in the aftermath. To ensure that these negative changes in trust are minimised, policymakers could ensure that *ex post* assistance are distributed in subgroups with greater potential for falls in trust and confidence.

9 CONCLUSION

This thesis provides evidence that natural disaster events have an impact on the levels of societal trust and institutional confidence in a population.

Using empirical methods as well as two case studies, I find that OECD regions generally experienced a fall in both the levels of societal trust and institutional confidence, whilst Non-OECD regions recorded a sizeable increase in trust and confidence. These findings are informative of the expectations surrounding the general trustworthiness of individuals and the effectiveness of a formal institutional response in the context of natural disasters. OECD regions, with strong institutions, would naturally have higher expectations of an effective formal institutional response in the aftermath of a disaster. A fall in the level of institutional confidence indicates that these formal institutions are failing to meet these expectations in OECD regions. Conversely, the increase in institutional confidence after a disaster indicates that the formal institutional response during the recovery went above the lower initial expectations in Non-OECD regions. This same intuition can be applied to the results of societal trust.

Importantly, I find that these changes in trust and confidence persist at least one year after a disaster. This persistence has implications when considering disaster policy measures. Policymakers in OECD regions must ensure that the level of institutional assistance in response to a large disaster is in line with these higher expectations to minimise any fall-out in confidence levels. The same thinking can be applied to Non-OECD regions, greater and more effective institutional assistance has the chance to build confidence. I also clarify these relationships for varying type of disaster events as well as for societies with economic, class and ethnic heterogeneities.

A possible extension of this research would be to investigate any heterogeneity that may arise from spatial distance to the disaster, possibly using ArcGIS technology. For this, one would need have precise data on the exact location of the disaster (epicentre) and the individual (distance to epicentre). One could then employ a regression kink discontinuity to calculate the true impact radius of the disaster. This would be useful when deciding on resource distributions pre and post disaster. Another extension could be to analyse the impact of disasters using a continuous treatment variable rather than the binary treatment used in Chapter 6. One could use Generalised Propensity Score (GPS) estimation to identify how changes in trust and institutional confidence vary according to the disaster intensity (Hirano & Imbens, 2004).

A final extension could track how disasters impact cooperative behaviours in the long term. I have shown that disasters have the potential to cause persistent changes in the level of trust one year on, but failed to detect any change in civic values. Young (2007, 2015) has provided a theoretical framework of how large exogenous events can often 'punctuate' social behaviours and set the stage for new behaviours to develop in the long-run. One could apply this same framework to the study of disaster impacts and cooperative social norms.

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A APPENDIX

A.1 DISASTER TIME SERIES

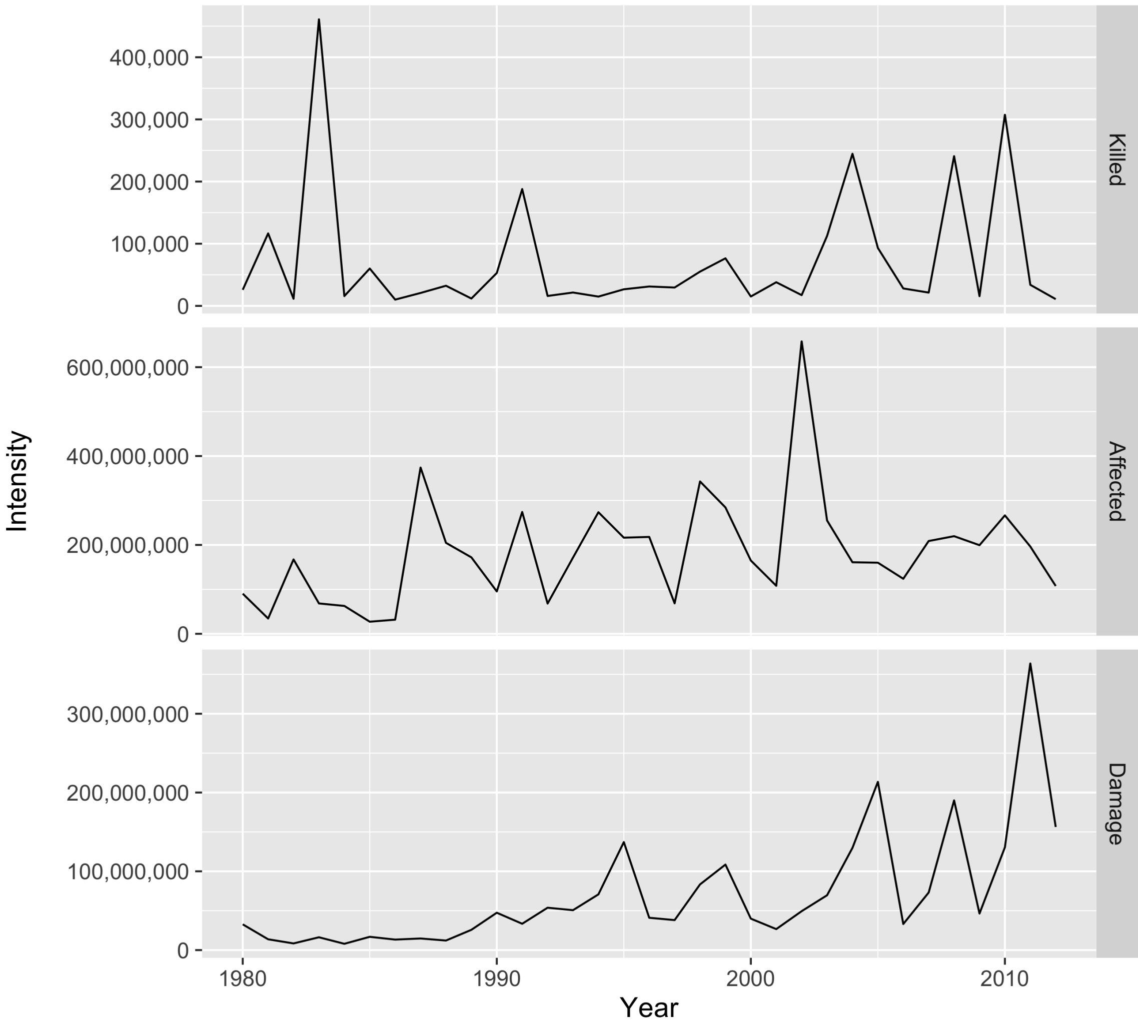

Figure 9: Natural Disaster Time Series

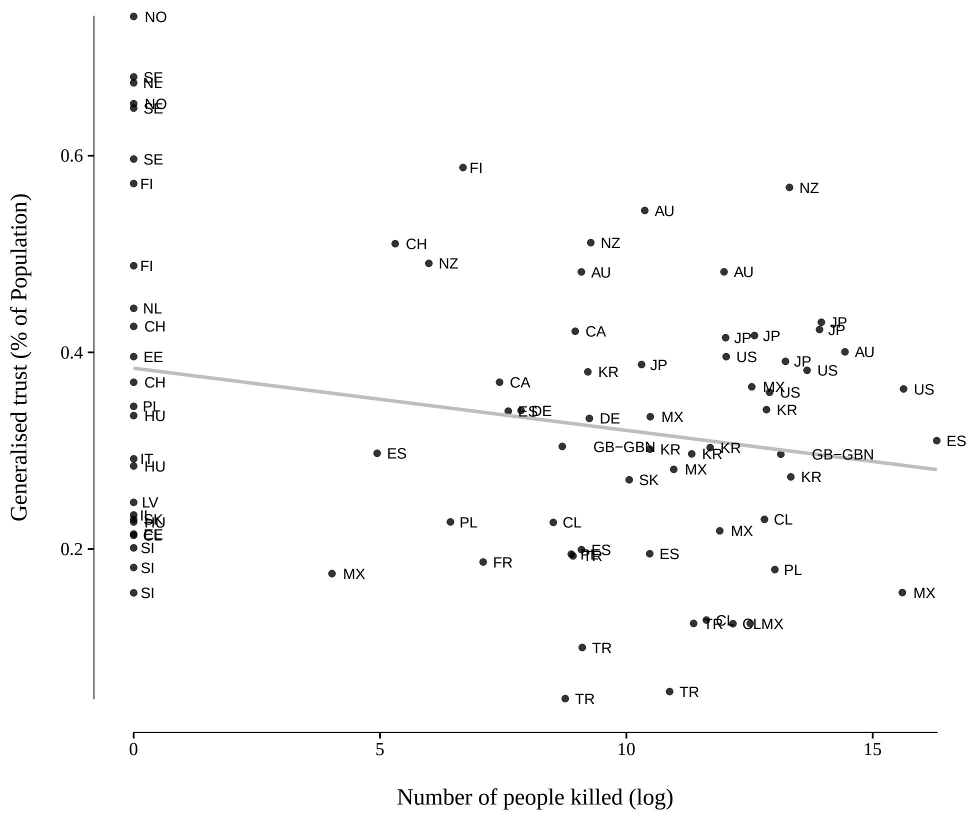

Figure 10: Generalised Trust and Disaster Intensity (Affected), OECD countries

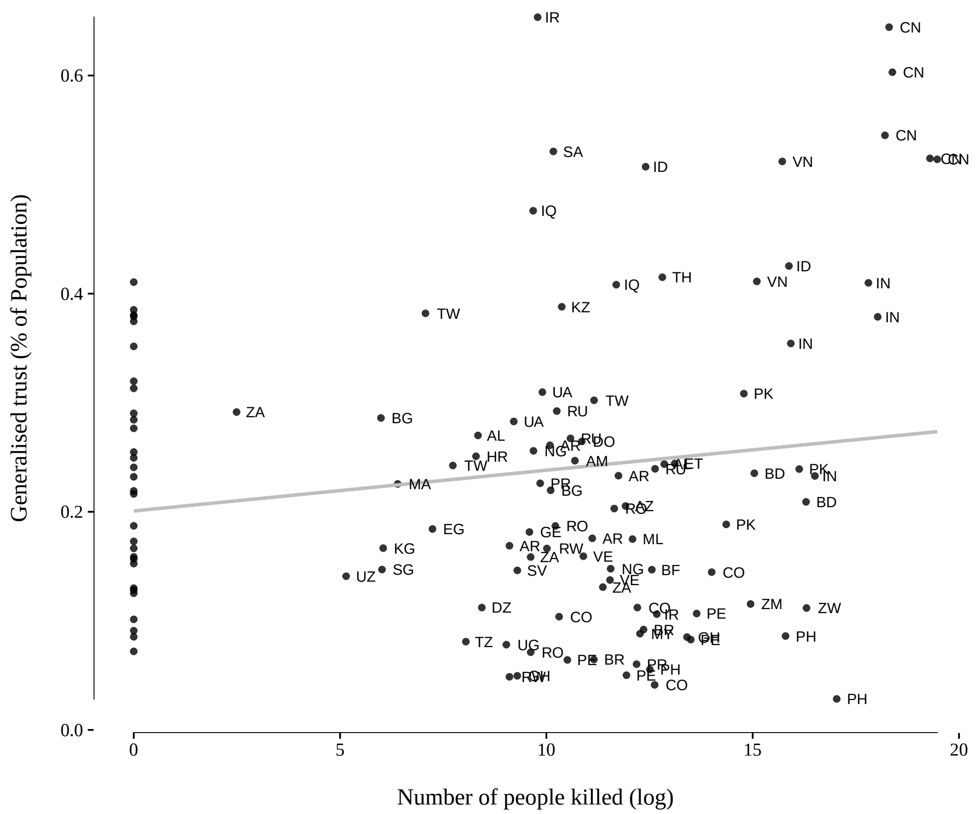

Figure 11: Generalised Trust and Disaster Intensity (Affected), Non-OECD countries

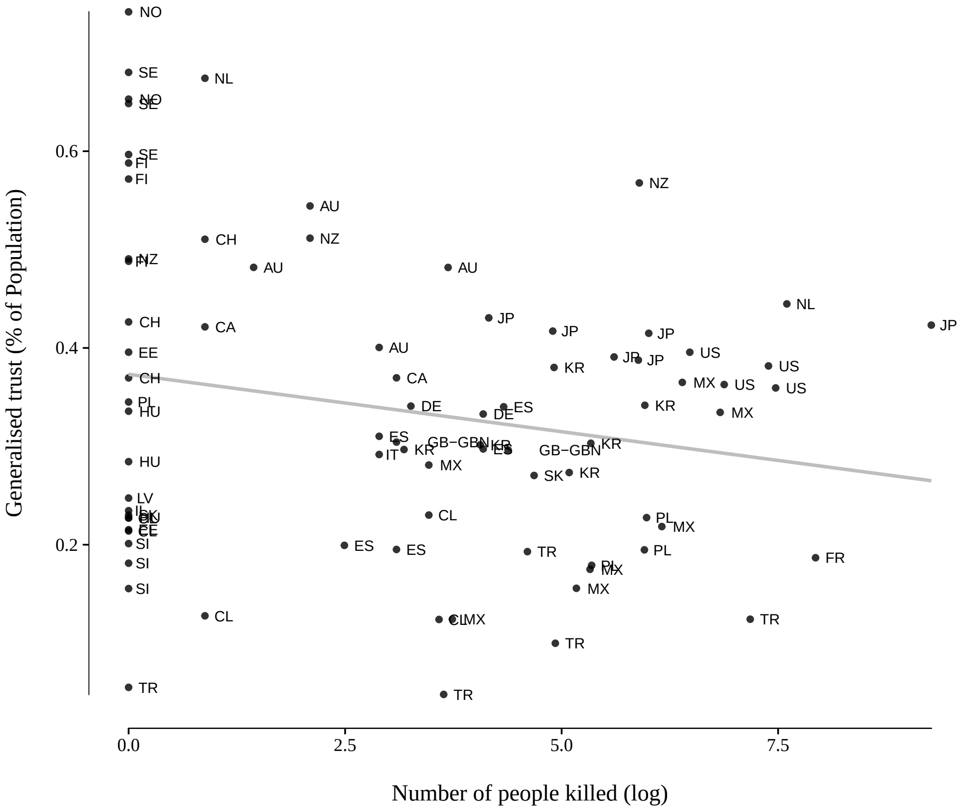

Figure 12: Generalised Trust and Disaster Intensity (Affected), OECD countries

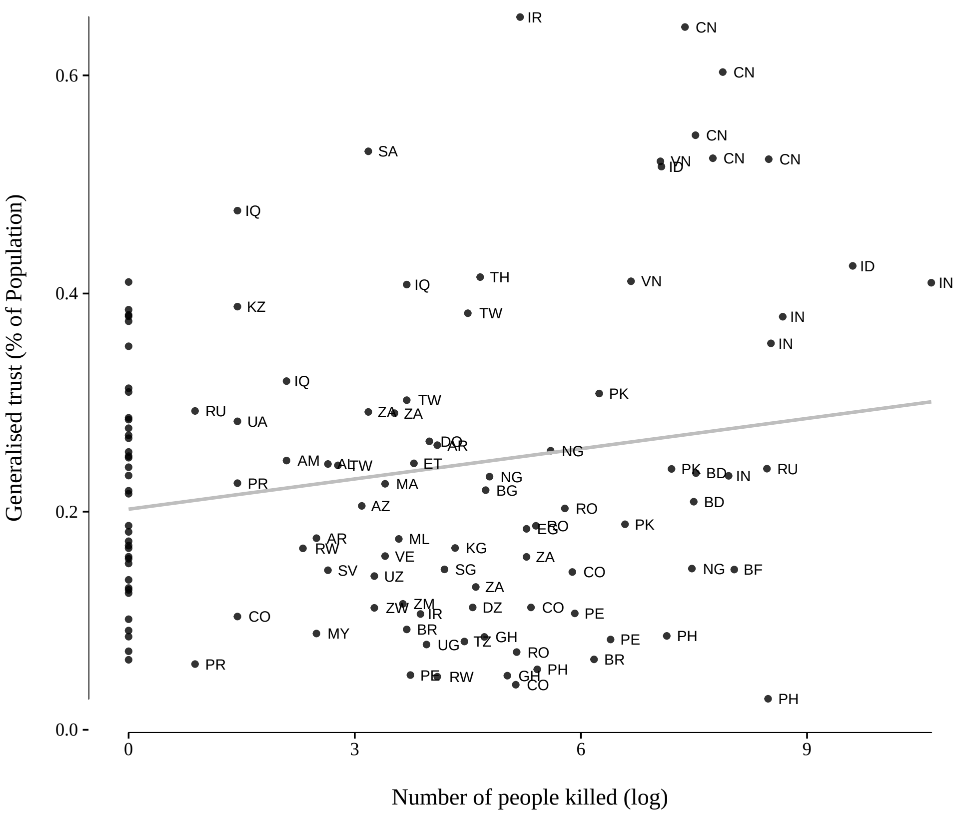

Figure 13: Generalised Trust and Disaster Intensity (Affected), Non-OECD countries

Table 26: Balance of Covariates - Disaster in Period t

	Untrimmed Sample			*Trimmed Sample*		
	Control	Treatment	t-stat	Control	Treatment	t-stat
Sex	0.48	0.50	-3.67^{***}	0.50	0.51	-1.66
			(0.00)			(0.10)
Age	41.13	41.67	-1.18	41.65	41.92	-0.56
			(0.24)			(0.58)
Education	4.61	4.71	-1.15	4.74	4.75	-0.07
			(0.25)			(0.94)
Income	4.56	4.70	-1.47	4.73	4.74	-0.16
			(0.14)			(0.87)
Religious	0.71	0.64	2.54^{***}	0.65	0.61	1.55
			(0.01)			(0.12)
Ethnic Fractionalisation	0.40	0.37	1.51	0.37	0.36	0.72
			(0.13)			(0.47)
Gastil Index	3.06	3.12	-0.40	3.04	3.25	-1.17
			(0.69)			(0.24)
Postcommunist	0.22	0.05	8.17^{***}	0.23	0.05	7.83^{***}
			(0.00)			(0.00)
Gini Coefficient	37.81	37.26	0.94	37.66	37.54	0.19
			(0.35)			(0.85)
Observations	1973	1973	1973	1211	1211	1211

Notes: ***Values in brackets under individual t-statistics are the associated p-values
***Significant at the 1 percent level.

The test conducted is a Welch two sample two-sided t-test, where the null hypothesis is that the difference in means between the two samples is 0. A statistically significant t-test indicates that the difference in means between the treatment and control is different from 0.

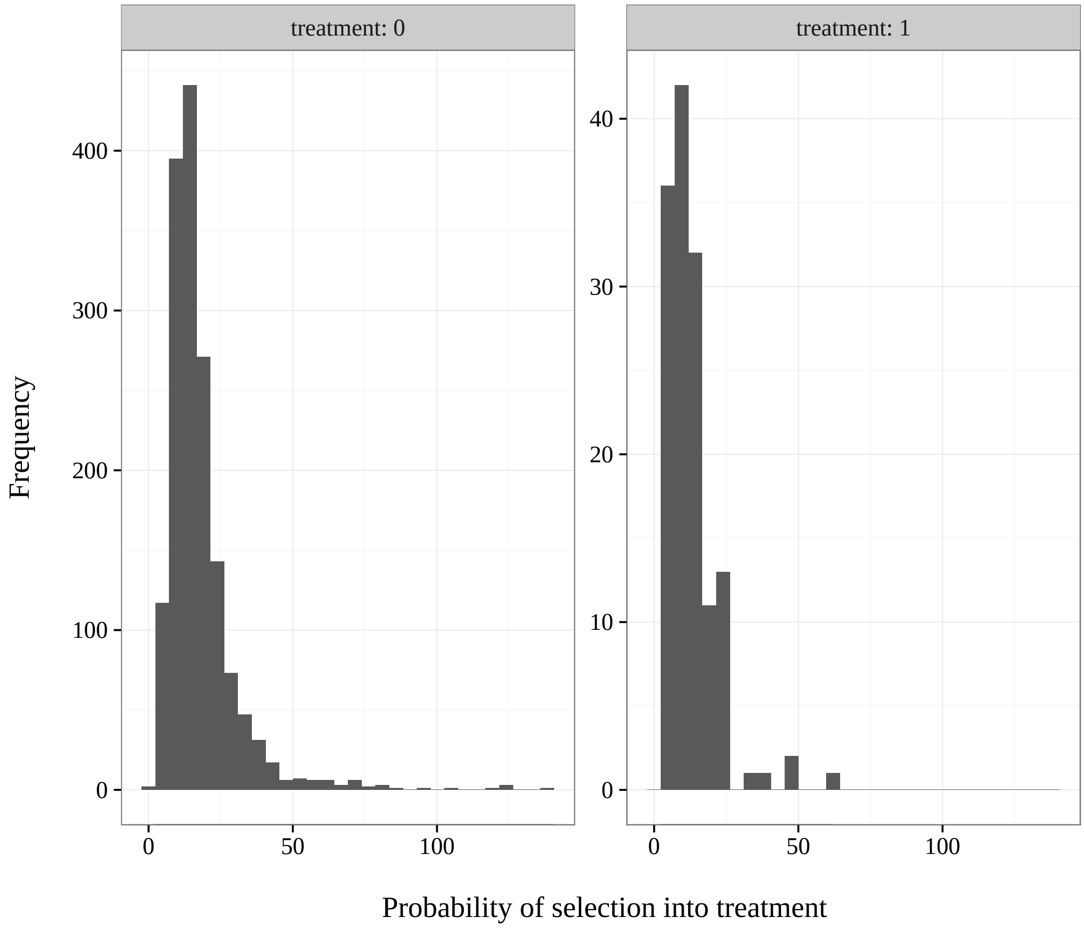

Figure 14: Histogram Inverse Propensity Scores - Disaster in Period t