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How Do Institutions Affect the Impact of Natural Disasters?

Abstract

In this paper we study how differences in the quality of countries' institutions affect the impact of natural hazards in these countries. To do so, we first build a new data set that allows us to adequately control for countries' development and geological characteristics and, importantly, the physical intensity of the natural hazard. We then analyze our data using an output distance frontier model to assess two important aspects of the relation-ship between institutions and hazard impacts. First, the model allows us to estimate the trade-offs between different types of (negative) outcomes (e.g., deaths, affected, and damages). Second, it enables us to estimate the excess deaths, affected inhabitants and damages that countries, all else equal, suffer relative to the best performing countries. We can refer to this as the countries' (in)efficiency at managing natural hazards. Our results show that countries differ a lot in their disaster management efficiencies, with richer countries performing better than poorer countries. Richer countries also incur higher capital losses in exchange for fewer lives affected, controlling for their overall level of development and population density. For rich and poor countries we show that institutions of higher quality indeed correlate with higher disaster relief efficiencies. Most important are indicators of good governance and government effectiveness, whereas the de jure indicators are not informative. Our estimates suggest that a country with a 10%higher disaster relief efficiency will save one more life and protect four more people at the cost of $8 million in capital losses in an average intensity natural hazard.

JEL-Codes: O440, Q450, E020.

Keywords: natural disasters, resilience, institutions, efficiency.

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1. Introduction

Natural disasters have become more frequent and more devastating in recent years. Moreover, climate change is predicted to cause the incidence and intensity of meteorological hazards to increase, and urbanization in the developing world implies that more, already vulnerable people will be exposed to their impacts (Loayza et al., 2012).

The evidence to date shows that the performance of countries differs greatly when it comes to disaster mitigation (Kahn, 2005; Toya and Skidmore, 2007). Some countries can quickly mobilize resources to support affected regions while others appear to be much less effective in handling disasters and as a consequence suffer much more severe impacts. However, the mechanisms behind these findings are not well understood. The logical next step in this literature is therefore to try and explain this heterogeneity by, controlling for hazard intensities, linking disaster impacts to the characteristics of the country it affected. We are not the first to do so. For a recent overview of this literature see Tol (2022).

Kahn (2005); Strömberg (2007); Noy (2009) provide a good starting point, they show in a cross-country panel that institutions play a mediating role and that countries with well developed institutions suffer fewer deaths from natural disasters. Countries with more democratic or higher institutional quality also experience fewer affected people in the case of a disaster (Persson and Povitkina, 2017). Similarly, Tennant and Gilmore (2020) show for tropical cyclones that effective institutions play an important role for the disaster risk reduction. However, if institutional quality is low they suffer more in democracies than in autocracies. In other words, disaster effects are more severe in countries that are poorly run. This has to do with the fact that some governments prepare well for disasters in the presence of international aid while others have no incentive to do so (Cohen and Werker, 2008). Related to this, Raschky (2008) finds that higher government stability and better investment climate decrease human and economic damage from disasters. While higher government effectiveness is connected to fewer people being killed and affected by disasters in the most vulnerable states (Sjöstedt and Povitkina, 2017).[1] Further, Breckner et al. (2016) provide insights into the role of institutional quality as a complement of insurance penetration in mitigating disaster effects. They demonstrate that insurance penetration reduces the negative economic consequences of disasters mainly in countries with good institutions, which they proxy by civil liberties or political rights.

A related strand of literature documents that natural disaster and extreme weather shocks lead to institutional change (Burke and Leigh, 2010; Brückner and Ciccone, 2011; Barone and Mocetti, 2014; Castells-Quintana et al., 2017) – Belloc et al. (2016) even observe a local institutional stagnation in response to earthquakes in medieval Italy – and pre-existing institutions serve as a source of differential effects. In regions with lower pre-quake institutional quality, corruption again distorts markets and deteriorates social capital, while technical efficiency increases in others due to financial aid and disruptive

[1] Keefer et al. (2011) provide evidence in relation to corruption. They show that non-corrupt systems are better prepared to deal with the consequences of earthquakes than corrupt regimes. While disaster mortality increases with inequality, corruption, and low-quality institutions (Escaleras et al., 2007; Anbarci et al., 2005).

creative mechanisms (Barone and Mocetti, 2014).[2] In a regional economic context, Testa (2021) demonstrates that major earthquakes have a negative impact on city population growth for those located outside of stable democracies. Weak institutions in combination with severe droughts paved the way for the Sicilian Mafia, at the expense of subsequent local development, as shown in Acemoglu et al. (2020). More generally, adverse temperature shocks increase the probability of coup d'états, resulting in negative impacts on economic growth (Dell et al., 2012).

The contrasting results from the related literature illustrate the need for a better understanding of the mechanisms that potentially link natural disasters to institutional quality and change. We address this matter in the current paper by introducing a new data set and analyzing it with a novel empirical method. Doing so, we can provide more precise estimates of the trade-offs among different disaster impacts and quantify the output elasticities for a range of disasters, regional characteristics, and the impact of institutional quality. To arrive at these contributions, we first build a unique data set that provides us with multiple measures of disaster characteristics and their consequences for countries worldwide. Next, we introduce the output distance stochastic frontier framework as an empirical approach for analyzing the data that has a number of important features. First, in this approach, we can handle multiple relevant disaster impacts (loss of lives, affected inhabitants, destruction of capital) simultaneously. This allows us to study important trade-offs in disaster relief efforts. Second, this method allows us to benchmark each country against a best practice frontier that is estimated controlling for the physical intensity of the event and important pre-shock features that are often hard to change. We will refer to these features as the country's 'hardware'. Third, with our approach we can estimate how the distance from the best performers is related to each country's 'software': the quality of its institutions. And finally, our model is flexible enough to allow us to investigate whether countries learn from events and close the gap to the best performers over time.

Compared to the existing literature, our approach - which to the best of our knowledge is the first application of frontier model techniques in this literature - has significant advantages. First, conventional studies exploring key factors behind the impact of natural hazards can only include a single dependent variable in each regression, such as the drop in the local GDP, total damages or the death toll (Kahn, 2005; Escaleras et al., 2007; Toya and Skidmore, 2007; Kellenberg and Mobarak, 2008; Cavallo and Noy, 2011; Cavallo et al., 2013; Kellenberg and Mobarak, 2011; Schumacher and Strobl, 2011; Strobl, 2010). Raschky (2008) and Felbermayr and Gröschl (2014) have multiple measures of hazard impacts in their data, but their main results still focus on impacts on economic growth, thereby ignoring the correlations and possible trade-offs between these different impacts. Using a model that incorporates several impacts into one estimation equation, we find that a decrease in the death toll along the frontier typically implies an increase in the material damage, for given levels of capital and income. Moreover, we can quantify these trade-offs. Second, the frontier model allows us to obtain unbiased estimates of trade-offs and marginal effects for the events and countries at the frontier. That is, for those observations for which we know the response was optimal, at least

[2] Connected to this, Klomp (2020) shows that election cycles and public spending provided in response to natural disasters have a stronger effect in countries with fewer checks and balances, such as presidential systems and majority elections.

among the observations in our data set. This gives us more precise estimates of such trade-offs and marginal effects in the presence of significant unobserved heterogeneity across events and countries. Third, the approach can handle significant unobserved heterogeneity by allowing for deviations from the frontier under some mild assumptions on the distribution of such deviations. This 'inefficiency' in the response to natural hazards is in principle an unexplained residual, but this can be explored further. The fact that institutional variables, especially those that reflect good governance, positively correlate with the estimated distance to the frontier suggests not only that our measure of disaster relief (in)efficiency makes sense, but also that it allows us to quantify how much improving institutions might contributes to countries' natural hazard resilience through this channel.

We report three major findings. First, we show countries differ a lot in their disaster-relief efficiencies, implying unobserved heterogeneity is significant. In our sample period from 1996 to 2010, New Zealand on average has performed best in disaster mitigation, followed by other developed nations such as Canada, Japan, and the United States. Emerging economies such as China, India, and Brazil usually have a middle rank between 20^{th} and 40^{th}, with developing countries in Sub-Saharan Africa typically closing the ranks. Second, institutional variables, especially governance quality indicators, such as government effectiveness, control of corruption, regime durability, voice and accountability, and regulatory quality, promote disaster-relief efficiency. In particular, a one standard deviation increase in the government effectiveness score leads to a 20% to 29% increase in the country's disaster relief efficiency while a one standard deviation increase in the control of corruption score implies a 24% to 33% increase in efficiency. Third, we find that more efficient countries tend to reduce human mortality while accepting higher economic damages in disaster mitigation. For example, we show that a 10% efficiency increase on average implies a 0.25% (0.3%) drop in the number of people killed (affected) and a 0.7% increase in material damages.

Our paper fits in the literature on the economic impacts of natural hazards and more specifically on the role that institutions play in mitigating their impacts (Besley and Burgess, 2002; Garrett and Sobel, 2003; Anbarci et al., 2005; Kahn, 2005; Strömberg, 2007; Kellenberg and Mobarak, 2008). Among them, our paper is most closely related to the seminal work of Kahn (2005) who specifically explored the relationship between governance quality and disaster mitigation. Studying 73 countries worldwide, Kahn (2005) points out that high income as well as good institutions lead to less people killed by natural disasters. Compared to the work of Kahn (2005), our paper uses a similar set of governance quality indicators, but extends his work in two important directions. First, we formally measure countries' disaster mitigation efficiencies and rank them against a common benchmark of best performers by employing a stochastic frontier model. Second, our data set includes data on the physical intensity of natural hazards, such that we can quantify the trade-offs between death toll, number of people affected and economic damages, controlling for hazard intensity [3]

The rest of our paper is organized as follows. Section 2 describes our data. Section 3 presents and motivates our empirical method. Section 4 presents our main results and

[3] Kahn (2005) only presents results including the Richter scale for earthquakes and concludes the elasticity of deaths to income per capita is robust to doing so, but it is not a priori clear that this also holds for the other types of events.

the final section concludes.

2. Data, Descriptive Figures, and Statistics

We construct our data by merging four data sets. We start by collecting disaster damages from the Emergency Events Database (EM-DAT) (Guha-Sapir et al., 2015). Our key explanatory variables are institutions, mainly the governance quality indicators from the World Bank. We control for macroeconomic variables from the Penn World Tables and disaster intensities from the GAME data set compiled by Felbermayr and Gröschl (2014). After merging the four data sets, we end up with 3,420 complete records on events over 15 years (1996-2010) in 159 countries (implying on average 1,43 events per country per year and 21,5 events per country, but the geographic distribution is very uneven).

2.1. Data for Disasters and Economic Variables

We follow Kahn (2005) and draw on the EM-DAT data set for our natural hazard impacts. EM-DAT contains the date and geographical location of natural hazards worldwide and reports the consequences of these hazards, notably including economic losses and the number of people killed and affected. EM-DAT registers an event if the reported death toll is above 1 or more that 10 people are affected or more than a million dollars in damages is reported. This sampling introduces some selection biases (see Felbermayr and Gröschl (2014) for a discussion), but as we run our analyses at the event level, this is not a major concern. Our source of data is the GAME data set presented in Felbermayr and Gröschl (2014). GAME reports the physical hazard intensity. Felbermayr and Gröschl (2014) collected primary data for all geophysical and meteorological events. This data set contains date and geographical location and adds disaster-specific intensity measures such as the magnitude of earthquakes, wind speeds for storms, and mean precipitation and temperature during months of flooding or drought. We believe it is essential to control for exogenous and physical disaster intensity when regressing disaster impacts on notoriously endogenous variables like income and institutional quality.

Figure 1 plots the counts of different types of disasters per continent. It shows that floods and storms are most frequent, accounting for almost 70% of the total events. The lower panel shows that Europe, after scaling for continent size, has the highest incidence of disasters. The most important take-away lesson from this figure is that rich nations, usually also with better institutions, do not experience fewer disasters or milder shocks than poorer nations, which is in line with the conclusion by Kahn (2005). Consequently, a country's economic strength and governance quality do not correlate with the incidence or intensity of hazards.

For our macroeconomic control variables, we turn to the Penn World Data (Feenstra et al., 2015). We control for a country's population density (total population/country area) and capital density (capital stock at current PPPs/country area) in the year of the event, because the higher the density of people and capital, the more human and material damage an event of given intensity is likely to create. That is, the same wind speed causes no damage in an empty desert whereas it can be very destructive in a densely populated urban center. We also control for GDP per capita because previous studies (Besley and Burgess, 2002; Kahn, 2005; Kellenberg and Mobarak, 2008) have

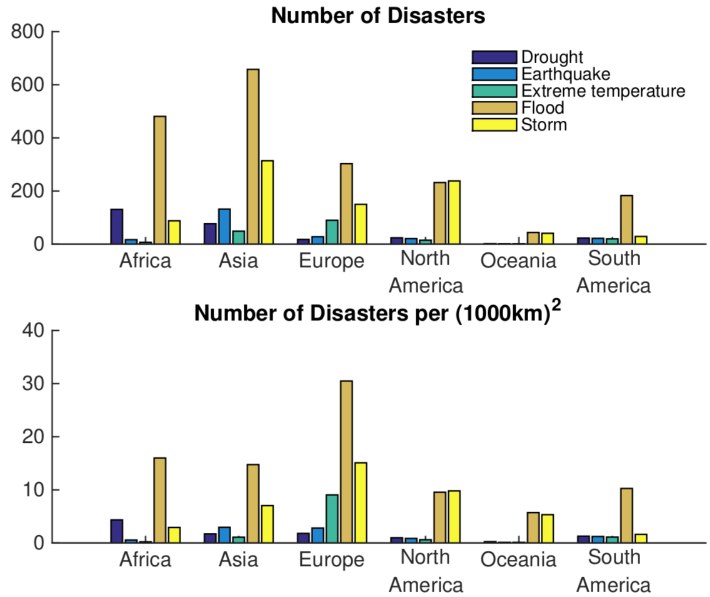

Figure 1: Disaster Distribution by Type and Continent. This bar chart plots the number of each type of disasters taking place in each of the six continents during 1996 to 2010 as well as the number scaled by continent size based on the EM-DAT data set. The figure shows that floods and storms are the most frequent events and Europe has the highest incidence of events per square kilometer.

shown that high income implies people are better protected against injury and death at the cost of higher property damage.

2.2. Institutions and Governance

The key explanatory variable in our study is institutional quality. There are many proxies for this elusive and multidimensional concept and we do not want to get bogged down in issues of definition here. Instead, we simply include several indicators compiled by the World Bank (Beck et al., 2001): *Government Effectiveness* and *Regulatory Quality* capture the capacity of the government to effectively formulate and implement sound policies; *Voice and Accountability* and *Regime Durability* indicate the process by which governments are selected, monitored, and replaced; and *Control of Corruption* represents the respect of citizens and the state for the institutions that govern economic and social interactions among them. These indicators were constructed based on survey data and refer to the quality of institutions as perceived by respondents in the respective countries.[4] In addition to these five indicators, we include the *Polity* score from the Center for Systemic Peace (CSP). A higher score on this indicator means that a country is more democratic while a lower score means the system is close to autocracy. Note that this indicator, in contrast to the World Bank indicators, reflects the de jure institutions in

[4]See Kaufmann et al. (2011) for a discussion of the data collection process.

the country and the CSP constructs these data based on legal analysis and constitutional characteristics, not survey data.[5]

2.3. Descriptive Statistics

Table 1 reports the summary statistics of our main variables for 3,420 events in 159 countries over the period 1996 and 2010. [6] Note that our unit of observation is a natural event, not a country-year observation. This implies that the mean for variables that are available only for a country (such as area) or country-years (such as GDP per capita) are not straightforward to interpret as they are weighted by the number of events in every country-year combination. What is clear from these statistics, however, is that our events affect rich and poor, densely and sparsely populated countries alike.

We can interpret the average event intensities and consequences. We see that mortality is greatly distorted by rare events, as the mean is even bigger than the value at the 90^{th} percentile. Probing the data, we find the largest death toll was caused by a drought and resulting famine in Ethiopia during 1983 and 1984. It killed more than 560,000 people. In contrast to mortality, the largest economic losses usually happen in developed nations. For example, the biggest-ever economic damage was caused by Hurricane Katrina in the U.S. in 2005, causing around $146 billion in damages. The following largest damages are related to the 1995 Kobe earthquake in Japan, the 1994 drought in China, and the 1998 country-wide floods in China. An important feature of our data is that we can now control for disaster intensity. Each type of disaster, however, has its own measure of intensity. As can be seen from the table, the average reported earthquake has a magnitude of 5.76 on the Richter scale. This is a score that can cause physical damage according to the description of the U.S. Geological Survey. The average and maximum wind speeds in reported storms are on average 62 and 150 knots, respectively, which is within the definition for hurricane winds according to the U.S. National Hurricane Center.[7] The average deviation of monthly rainfall from the local, long-run (1970-2010) mean is -0.09 mm for a drought and +0.20 mm for a flood event. Meanwhile, extreme temperature events have a mean monthly difference of -0.09 °C (more cold spells than heat waves in our data) and the average divergence for droughts is -0.14 °C, due to a few large negative deviations.

To illustrate the pattern among the three disaster impact measures, we plot them in Figure 2. The Figure shows the median values for each measure across different continents. The immediate impression is that African and Asian countries usually suffer from high mortality, whereas Europe and North America mainly experience economic losses. This pattern suggests that a trade-off exists among different damage measures. This poses a problem for our estimation: when we regress the impacts on intensities and country level variables in three separate equations, we will obtain three different sets of coefficients, making conclusions inconsistent. We therefore propose to use the output

[5] See the website of the Center for Systemic Peace (http://www.systemicpeace.org) for a discussion of the data collection process.

[6] Although the development indicators begin at 1979, the institutional variables are available only since 1996. Merging data sets gives us the advantage of exploring the relationship between institutions and disaster relief but also results in a significant loss of observations. When there is a missing value in any one of the variables for an observation, we drop that observation.

[7] See https://www.nhc.noaa.gov/aboutsshws.php.

Table 1: Summary Statistics

	Average	Standard Deviation	Minimum	10^{th} Percentile	Median	90^{th} Percentile	Maximum	Observations
Pre-conditions								
GDP per capita ($)	9727.505	11651.360	166.866	847.072	4820.058	29600.9	93496.54	3420
Population (in millions)	144.059	311.913	0.044	3.817	32.652	285.796	1340.969	3420
Capital stock (2011 U.S. $ trillions)	4.079	9.225	0	0.024	0.764	10.406	50.007	3420
Country area (km^2 millions)	1.907	3.405	0	0.032	0.397	9.148	16.889	3420
Population density (#people/km^2)	251.765	1067.132	0.667	13.068	84.990	372.788	13871.67	3420
Capital density ($ thousands/km^2)	8.115	30.450	0.004	0.128	1.368	17.760	477.611	3420
Earthquake magnitude	5.759	1.017	2.7	4.4	5.8	7.1	8.6	206
Maximum wind speed of storm (km/h)	61.778	25.894	9.7	29.9	57.9	96	150	837
Diff. monthly temperature drought (in °C)	-0.139	2.250	-35.575	-0.083	0.012	0.100	2.598	255
Diff. monthly temperature ex-weather (in °C)	-0.088	2.759	-21.662	-0.164	0.023	0.544	9.178	187
Diff. monthly rainfall drought (in mm)	-0.092	0.507	-0.941	-0.617	-0.126	0.338	4.695	277
Diff. monthly rainfall flood (in mm)	0.202	0.539	-0.848	-0.206	0.101	0.707	13.549	1889
Institutions								
Government effectiveness	0.003	0.896	-1.982	-0.954	-0.171	1.603	2.357	3420
Control corruption	-0.129	0.925	-1.979	-1.055	-0.399	1.417	2.525	3420
Regime durability	22.712	25.821	0	2	11	49	98	2975
Voice and accountability	-0.063	0.913	-1.948	-1.324	-0.107	1.276	1.768	3420
Regulatory quality	0.012	0.869	-2.261	-1.056	-0.158	1.417	2.023	3420
Polity score	0.735	0.290	0	0.2	0.85	1	1	3340
Disaster consequences								
Number of people killed	379.448	6196.775	1.000	2.031	13.547	156.384	230659.4	2377
Number of people affected	1397.656	11857.540	0.001	0.203	9.954	717.749	314391.6	2876
Economic damage ($ millions)	1117.843	5529.870	0.005	1.889	101.195	2097.366	146303.1	1327

Notes: This table summarises descriptive statistics for the variables used in the baseline analyses. The sample includes three measures of disaster damage (the number of people killed, economic damage, and the number of people affected). The institutional variables stem from the World Bank database. The natural hazard intensities are collected from the GAME data set, and the economic pre-conditions stem from the Penn World Tables. The sample covers 3,420 events in 159 countries between 1996 and 2010.

Figure 2: Continents Feature Different Types of Damages. This bar chart plots the median values of each of the three damage measures (number of people killed (in hundreds), number of people affected (in million), and economic damage (in billion dollars)). We scale killed and affected people to improve the readability of the figure. The data source is the EM-DAT dataset with the time horizon from 1996 to 2010. The figure indicates that for African countries the biggest consequence of disaster is massive mortality, whereas Europe and North America, compared to other continents, have relatively high economic losses in terms of GDP.

distance frontier model that can incorporate multiple outcomes into one equation. In this model we can simultaneously estimate the distance to the frontier and quantify the trade-offs at that frontier. As detailed in our results section, we show that a reduction in the gap may mean a significant drop in mortality yet imply an increase in property damages. The next section presents this method more formally.

3. Empirical Methodology

3.1. The basis for our approach

Our methodological approach starts from the fact that we are dealing with extreme events. Therefore, a method that is at its most informative with an average response function to an average event will not suffice. Indeed, even a local average response function may mean we miss the most important reactions to the most important events. Instead, we need a method that informs us about the inefficient, off-center response to extreme events. The first key to understanding our approach is to think of countries' ability to cope with hazards as a time varying, not necessarily normally distributed omitted variable that itself encapsulates different aspects, many of them related to institutional arrangements in those countries. The second key is the realization that an extreme event 'produces' multiple types of impacts: deaths, injured citizens, and material damage. Our model should be able to assess the consequences for each type of impact in the following ways. First, it should allow for a trade-off between the different types of impact y_i, while acknowledging that these different types of impact are not independent of each other. Second, it should isolate the moderating effect of 'software' (institutional choices of countries) z_i on countries' efficiency to cope with natural hazards. Third, it should allow for countries' 'hardware' x_i to directly affect each type of impact.

3.2. Two important technical aspects

Before we introduce the model formally, let us take a moment to consider two technical aspects that will turn out to be crucial features of the model. The first one concerns our use of a so-called 'Euclidean norm' to combine different types of impact. Our goal is to estimate the optimal impact of a natural hazard, i.e., the impact with the least consequences in terms of deaths, affected citizens, and material damage. We also want to know for each country at each point in time, how far away it is from that optimum. Since the optimal impact is measured along multiple dimensions, we need a measure that convincingly combines these dimensions. Hence, we turn to the Euclidean distance, similar to what is used for example in many cluster analyzes. More specifically, since the optimal impact of a hazard is the one with the least deaths, injured citizens, and material damage, we use the inverse of the Euclidean norm of the disaster output vector that consists of deaths, injured citizens and material damage.[8] As a result, the model we use is a so-called output-distance model, a particular type of production model that allows us to estimate a single equation for a process that has three jointly produced outputs. One of the advantages of this model is that we can also estimate the relationship between each of the outputs, including possible trade-offs. For example, when more higher quality buildings result in less deaths but more material damage after a disaster, an output-distance model allows us to estimate the elasticity of substitution between these impacts at the efficient frontier.

The second technical aspect of our model concerns the crucial omitted variable: the efficiency term that measures the distance to the 'optimal', best-practice mix of outputs for a given disaster. For that, we use a deconvolution technique, similar to what is known for example in a random effects panel model, where a standard noise term is replaced by a joint error term that captures a shared noise element and a (firm-, country- or otherwise-) specific noise element. Here, we opt for a different type of convolution. After all, the disaster efficiency of a country is not directly observable, but we know that the most efficient that a country can be in handling a natural hazard is when it has the mix of impacts that is predicted by the output-distance model. As a consequence, we aim to deconvolute the standard noise term of that model to distinguish between two very different aspects. The first is the standard noise term, that is normally distributed, has a mean of zero, and captures among other things measurement error. The second is an inefficiency term, that is truncated normally distributed, since a country either has the optimal impacts mix or something that is worse (i.e., an impact mix that has more deaths, affected or damages than the best performers in our data set). Fortunately, this kind of deconvolution has become standard practice in a large part of the productivity literature, based on what has become known as stochastic frontier analysis. [9] In that literature, the resulting stochastic frontier model can identify trade-offs and inefficiency exactly because (we assume) noise and inefficiency have different distributions.

[8] See Section 3.2 of Kumbhakar and Knox-Lovell (2000) for more details.

[9] See, e.g., Aigner et al. (1977),Meeusen and van Den Broeck (1977),Färe and Primont (1990),Kumbhakar and Knox-Lovell (2000)

In our model, we combine both aspects to arrive at an approach that is both advanced and - as we will see later - straightforward to interpret.

3.3. Model setup

We start with a standard expression of a production function:

$$\boldsymbol{y}_{j,i,t} = f(\boldsymbol{x}_{j,i,t}; \beta) \cdot \exp\{v_{j,i,t}\}, \tag{1}$$

where $\boldsymbol{y}_{j,i,t}$ is our vector of different types of impact for a disaster j in country i at time t. For our setting with three impacts, we have $\boldsymbol{y}_{j,i,t} = y^1_{j,i,t}, y^2_{j,i,t}, y^3_{j,i,t}$. Likewise, $\boldsymbol{x}_{j,i,t}$ is a 'hardware' vector that includes both hazard intensity and country characteristics. and $v_{j,i,t}$ is a normally distributed noise term with mean zero. The model at this stage is multiplicative, but when we arrive at a full specification and take logs of the variables in both vectors $\boldsymbol{y}_{j,i,t}$ and $\boldsymbol{x}_{j,i,t}$, it will start to look much more like a standard regression model.

To illustrate our modeling approach, it proves useful to first write equation (1) as:

$$\frac{\boldsymbol{y}_{j,i,t}}{f(\boldsymbol{x}_{j,i,t}; \beta)} = \exp\{v_{j,i,t}\}. \tag{2}$$

If there is no noise, $\frac{\boldsymbol{y}_{j,i,t}}{f(\boldsymbol{x}_{j,i,t};\beta)} = 1$, so $v_{j,i,t} = 0$ and all countries with the same set of $\boldsymbol{x}_{j,i,t}$, will have the same $\boldsymbol{y}_{j,i,t}$. In practice, of course, that is not - necessarily - the case. and:

$$\frac{\boldsymbol{y}_{j,i,t}}{f(\boldsymbol{x}_{j,i,t}; \beta)} = D_0(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta), \tag{3}$$

where D_0 is defined as the Euclidean distance between the predicted $\hat{y}_{j,i,t}$ and the actual $\boldsymbol{y}_{j,i,t}$ for the same $\boldsymbol{x}_{j,i,t}$. That distance will be zero under two conditions. First, any noise should on average be zero (and symmetrically distributed). Second, as mentioned, all countries with the same set of $\boldsymbol{x}_{j,i,t}$ should have the same $\boldsymbol{y}_{j,i,t}$. The first condition is met when we assume a standard error term. The second condition is met if all countries are equally efficient at handling natural hazards. If it is *not* met, there is inefficiency. For now, let us denote that inefficiency by $u_{j,i,t}$. Then we can write:

$$D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta) = \exp\{v_{j,i,t} - u_{j,i,t}\} \tag{4}$$

Or equivalently:

$$1 = D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta) \cdot \exp\{u_{j,i,t} - v_{j,i,t}\}. \tag{5}$$

Recall that D_o is the distance to the optimal mix of disaster outcomes (deaths, injured people, material damage) for the given mix of hardware $x_{j,i,t}$. As explained by Kumbhakar and Knox-Lovell (2000), since $D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta) \leq 1$, $\exp\{u_{j,i,t} - v_{j,i,t}\} \geq 1$. That means that the second condition is only expected to hold if $E(u_{j,i,t}|u_{j,i,t} - v_{j,i,t}) = 0$, since $E(v_{j,i,t}) = 0$ by its definition of being a normally distributed noise term with mean zero. In the presence of inefficiency for at least some countries, $E(u_{j,i,t}|u_{j,i,t} - v_{j,i,t}) \geq 0$, and $u_{j,i,t}$ is an output (i.e., hazard impact) oriented measure of technical efficiency, exactly as in standard stochastic frontier analysis. Where we have made use of the second technical aspect described above.

To turn equation (5) into a full-fledged empirical model, we turn to the first technical aspect. Recall that we can use the reciprocal of the Euclidean norm of $y_{j,i,t}$ to capture the distance to the frontier in the multiple dimensions of $y_{j,i,t}$. Again following Kumbhakar and Knox-Lovell (2000), we introduce a parameter λ and make use of the fact that:

$$D_o(\boldsymbol{x}_{j,i,t}, \lambda \boldsymbol{y}_{j,i,t}; \beta) = \lambda D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta), \quad \lambda > 0 \tag{6}$$

The reciprocal of the Euclidean norm of $\boldsymbol{y}_{j,i,t}$ then says that:

$$\lambda = |\boldsymbol{y}_{j,i,t}|^{-1} = \left(y^1_{j,i,t} + y^2_{j,i,t} + y^3_{j,i,t}\right)^{-\frac{1}{2}}. \tag{7}$$

And so we can write:

$$|\boldsymbol{y}_{j,i,t}|^{-1} \cdot D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta) = D_o(\boldsymbol{x}_{j,i,t}, \frac{\boldsymbol{y}_{j,i,t}}{|\boldsymbol{y}_{j,i,t}|}; \beta). \tag{8}$$

At this stage, we have two more steps to go through before we can start estimating our model. First, we must parameterize our model and propose an empirical specification. Second, we must fine tune that empirical specification to further suit our needs in order to assess how institutions affect the efficiency of disaster relief.

3.4. Empirical specification

To arrive at an empirical output distance frontier, we make use of two properties of the output distance model: D_o is linearly homogenous of degree 1 in all y and we can write the distance function as a function of $\boldsymbol{x}_{j,i,t}$ and $\boldsymbol{y}_{j,i,t}$, i.e., $D = f(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t})$. Therefore, we have:

$$|\boldsymbol{y}^1_{j,i,t}|^{-1} \cdot D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta) = f(\boldsymbol{x}_{j,i,t}, \tilde{\boldsymbol{y}}_{j,i,t}), \tag{9}$$

where $\tilde{\boldsymbol{y}}_{j,i,t}$ is now the normalized output vector of the remaining impacts, i.e.,

$$\tilde{\boldsymbol{y}}_{j,i,t} = \left(\frac{y^2_{j,i,t}}{y^1_{j,i,t}}, \frac{y^3_{j,i,t}}{y^1_{j,i,t}}\right). \tag{10}$$

The next step then consists of converting equation (9) into logs and employing a translog specification for the functional form f. A major benefit of a flexible functional form like the translog is that it will allow us to inspect both the interactions between the hardware variables $x_{j,i,t}$ and the impact of a specific disaster $y_{j,i,t}$ as well as the interactions (and trade-offs) between those disaster impacts at the frontier.

Before we do so, recall that $D_o(\boldsymbol{x}_{j,i,t}, \boldsymbol{y}_{j,i,t}; \beta) = \exp\{v_{j,i,t} - u_{j,i,t}\}$. Therefore, $\ln D_o = -u_{j,i,t}$ and can be moved to the right hand side (where it then changes sign) and estimated as part of the residual of the resulting translog model, so we arrive at:

$$\begin{aligned} -\ln y^1_{j,i,t} = \alpha_0 &+ \sum_{k=1}^{K} \alpha_k \ln x^k_{j,i,t} + \sum_{m=2}^{3} \beta_m \ln \hat{y}^m_{j,i,t} + \frac{1}{2}\sum_{k=1}^{K}\sum_{k'=1}^{K} \alpha_{kk'} \ln x^k_{j,i,t} \ln x^{k'}_{j,i,t} \\ &+ \frac{1}{2}\sum_{m=2}^{3}\sum_{m'=2}^{M} \beta_{mm'} \ln \hat{y}^m_{j,i,t} \ln \hat{y}^{m'}_{j,i,t} + \frac{1}{2}\sum_{k=1}^{K}\sum_{m=2}^{3} \alpha_{km} \ln x^k_{j,i,t} \ln \hat{y}^m_{j,i,t} + u_{j,i,t} + v_{j,i,t}. \end{aligned} \tag{11}$$

As the final steps in our modeling process, we revisit the unit of observation in our analysis and explain how we introduce 'software' - institutional variables - in our model.

3.5. Finetuning our approach

In our model, hazards j in countries i at time t are in the driver's seat. These hazards potentially cause damages, hurt, and kill people. It is up to countries to build institutions to decrease the impact of these hazards. The best mix of institutions makes a hazards less destructive. Of course, countries are also affected differently by disasters for reasons that are beyond their control and/or hard to grasp in an empirical analysis. Also, over time, developments such as, for example, new vintages of physical capital may change the impact of a disaster. For those reasons, the first way we fine tune our approach is by replacing the standard intercept α_0 by α_i and α_t - country and year fixed effects.[10]

Finally, in Equation (11), efficiency is $u_{j,i,t} \geq 0$. It has a truncated normal distribution, $|N(\mu_{j,i,t}, \sigma^2_{j,i,t})|$, with the truncation point at $\mu_{j,i,t}$. The larger $\mu_{j,i,t}$, the less efficient is the entire distribution containing all disasters on average. More important for our purposes, in our model this truncation point is determined by an institutional variable $z_{i,t}$:

$$\mu_{j,i,t} = \delta + \eta z_{i,t}. \tag{12}$$

Our coefficient of interest is η, which we expect to be negative. That is, better institutions should reduce the efficiency of hazards in creating negative impacts. Note that $z_{i,t}$ does not have a subscript j, since institutional variables are country specific but not disaster type or event specific. Since institutional variables are often correlated, we estimate our model with each of the institutional variables of choice separately, in order to be able to quantify the effect of each individually. To account for a possible second-moment effect, we further allow the variance of inefficiency to be determined by institutions as well:

$$\sigma^2_{j,i,t} = \exp(\lambda + \psi z_{i,t}). \tag{13}$$

Both equations (12) and (13) are estimated with maximum likelihood methods in a single step with (11).

4. Results

In this section, we present our key results on the average efficiencies of countries in disaster mitigation. Then, we turn to the role played by good governance in promoting such efficiency.

4.1. How Does the "Hardware" Shape the Frontier?

Table 2 presents our results. Column (1) uses a simple OLS framework without efficiency estimation as a starting point. Columns (2) to (7) use stochastic frontier models and estimate the effects of governance quality on efficiencies. Results are robust across models, as can be noticed from the similar signs and magnitudes of coefficients for each variable.

[10]Note that we actually observe the precise month in which a disaster takes place. However, in our entire data set there is no month (for any country) where multiple disasters of different types take place, so it will not make a difference if we introduce month fixed effects.

Before we discuss results in more detail, it is important to remember why we care about the shape and the location of the frontier. We build a frontier using a vector of what we have termed 'hardware' variables to separate the impact of wealth from development. Given that the per capita income and concomitant amount of capital is much higher in some countries than in others, our estimates place countries on or below the frontier where they are surrounded by countries with a similar 'hardware' set. If, later on, we find that more developed countries are more resilient to natural hazards than less developed countries, this indicates that it is not sheer wealth, but also the way this wealth has been put to use, for example, by investing in capital (buildings, etc.) of a higher quality.

As for the estimates on the disaster intensities, the effects of earthquakes and storms are highly statistically significant in all models, but with a small magnitude. For instance, a 1 point (about one standard deviation at the mean) increase in earthquake magnitude leads to a 0.35% increase in damage. [11] Similarly, a one standard deviation increase in wind speed (about 26 km/h) causes a 0.13% to 0.16% increase in damage. Rainfall shortage affects damage significantly in some models: the signs are uniform and the economic magnitude is large. On average, a 10mm less in monthly rainfall from the mean implies a 30% increase in damage.[12] Using column (2) as an example, a 1% increase in population density (number of people per km^2) and GDP per capita (dollars) on average leads to a 38% and 51% increase in damage (millions of dollars), respectively.

4.2. How Efficient are Countries in Mitigating the Impact of Disasters?

After discussing the shape and location of the frontier, we now turn to the distance of countries to the frontier. We are interested in the global spread in efficiency scores for two reasons. First, we want to know how much development correlates with efficiency - after controlling for countries' 'hardware'. Second, the shape of the global efficiency distribution conveys us with an idea of the overall unconditional opportunities for countries to advance in building natural hazard resilience.

Table 3 presents the efficiency value for each country averaged over the sample period (1996 to 2010). The numbers reported in columns (1) to (5) are similar: they all point out that countries like New Zealand, Switzerland, Austria, and the U.K. are quite efficient in disaster relief. With efficiency values between 70% and 90%, these countries' actual impacts are very close to the minimum impact frontier. Transition economies such as China, India, and Brazil usually occupy a middle rank between 20^{th} and 40^{th}. In general, the efficiency ranking is closely related to the development level, with more developed nations ranking at the top. The last column using the polity score in the stochastic frontier estimation, is less revealing. Not only is the ranking less intuitive, but also efficiency values are generally very high. [13]

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[11] It is important to note that the Richter Scale is an exponential scale, i.e. a 6 point earthquake is ten times more intense than a 5 degree earthquake. Therefore, we took the base-10 logarithm in the estimations.

[12] Here, "Diff. monthly rainfall drought" means difference in monthly rainfall in mm from the long-run monthly mean, 1979-2010. When interpreting this coefficient, it is important to note that the positive sign means that more rainfall reduces the damage of drought, as expected; an excessive shortage of rain increases the damage.

[13] A reason might be that the polity score was created to measure the durability of institutional

Table 2: Effects of Institutional Variables on Disaster Relief Efficiency Estimated by Output Distance Frontier Method

Frontier	(1) OLS	(2) Government effectiveness	(3) Corruption control	(4) Voice and accountability	(5) Regulatory quality	(6) Regime durability	(7) Polity score
Earthquake magnitude	0.110***	0.124***	0.117***	0.122***	0.120***	0.099**	0.110***
	(0.042)	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)	(0.039)
Maximum wind speed	0.005***	0.006***	0.006***	0.006***	0.006***	0.001	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Diff. monthly temperature	-1.440	-1.234	-1.400	-1.752	-1.408	-1.469	-1.243
- drought	(3.906)	(3.801)	(3.899)	(4.165)	(3.780)	(3.960)	(3.899)
Diff. monthly temperature	-22.443	-25.878	-25.253	-20.229	-23.866	-28.589	-21.321
- extreme weather	(19.712)	(19.773)	(20.056)	(19.074)	(19.051)	(18.861)	(18.107)
Diff. monthly rainfall	-2.476	-2.751	-2.412	-3.026*	-2.350	-2.450	-2.820*
- drought	(1.702)	(1.745)	(1.774)	(1.737)	(1.659)	(1.674)	(1.655)
Diff. monthly rainfall	0.288	0.313	0.330	0.339	0.323	0.377	0.331
- flood	(0.249)	(0.233)	(0.231)	(0.230)	(0.234)	(0.231)	(0.234)
η (inefficiency mean)		-1.529**	-1.252***	-1.585***	-0.997**	-0.200***	-33.027
		(0.641)	(0.408)	(0.520)	(0.482)	(0.056)	(98.013)
ψ (inefficiency variance)		-0.444	-0.631	-0.294	-0.452	0.003	1.826
		(0.478)	(0.413)	(0.270)	(0.519)	(0.004)	(4.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	654	654	654	654	654	569	654
Log Likelihood	-1162	-1157	-1156	-1155	-1159	-1008	-1160
Wald χ^2		1262	1255	1223	1277	1075	1375

Notes: This table reports the effects of countries' institutional variables on their disaster relief efficiency using the output distance frontier method. We include worldwide disaster events taking place between 1996M1 and 2010M12 and control for countries' natural and economic pre-conditions. The institutional variables include measures of government effectiveness, control of corruption, regime durability, voice and accountability, regulatory quality, and the level of democracy (the polity score), as reported in the World Bank dataset. Natural pre-conditions, e.g. mean temperature difference, mean precipitation difference, are from the EM-DAT database, and economic control variables (with interaction terms, not reported for readability), e.g. population, capital stock, GDP per capita, country area, are from the Penn World Table. As we have three measures of disaster damage (i.e. number of people killed, monetary damage, and number of people affected), we choose the output distance frontier method, a modified stochastic frontier approach that helps us to estimate efficiency using a single equation. We impose a rather loose assumption that inefficiency has a truncated-normal distribution while letting the model determine the location of the truncation point, which is a function of our institutional variables. We manually adjusted the signs on coefficients of disaster variables such that they correspond to $\ln(damage)$ (the dependent variable in the derived original regression equation is $-\ln(damage)$). For each institutional variable, the effect on the mean of the inefficiency is reported at the first two rows whereas the effect on the variance of the efficiency is reported at the second two rows. The standard errors are reported in parentheses. All the regressions control for the country fixed effects.

To better understand the global picture, we plot the distribution of efficiencies for all countries in Figure 3 for each institutional measure. The first five histograms unanimously show that there is a concentration in the low efficiency region. Moreover, a large number of countries are either very efficient or very inefficient. The 'missing' middle contains relatively few countries, suggesting that the transition from fragility to resilience is not gradual.

4.3. How Does the "Software" Affect the Distance to the Frontier?

Given the differences in development, the large variation in estimated disaster relief efficiencies suggests that a country's "software" variables play a role in explaining this heterogeneity. The lower part of Table 2 reports the estimated effects of institutional variables on inefficiencies. A negative η indicates that the institutional factor z makes the country *less* inefficient. Indeed, we find a significantly negative relationship between disaster-relief inefficiency and institutional quality, for government effectiveness, control

frameworks. Hence, it captures the de jure aspect, which might be less informative related to our question. The variability in the Polity index for countries at the very top or bottom of the ranking is lost and coding of the Polity index can be discussed, particularly for occupied countries or countries in a conflict situation; see Boese (2019) for a full discussion.

Table 3: Efficiency Ranks

(1) Government effectiveness		(2) Control corruption		(3) Voice and accountability		(4) Regulatory quality		(5) Regime durability		(6) Polity score	
New Zealand	0.78	New Zealand	0.89	New Zealand	0.75	U.K.	0.76	New Zealand	0.77	Congo	0.93
Austria	0.78	Switzerland	0.82	Switzerland	0.73	New Zealand	0.74	Canada	0.75	Argentina	0.93
Switzerland	0.77	Austria	0.82	Canada	0.72	Switzerland	0.70	U.K.	0.75	Malaysia	0.93
Canada	0.77	Canada	0.82	Australia	0.70	U.S.	0.69	Australia	0.74	Russia	0.93
U.K.	0.73	Germany	0.79	Belgium	0.68	Austria	0.69	Switzerland	0.74	Colombia	0.93
Germany	0.72	Australia	0.78	Germany	0.68	Australia	0.68	Belgium	0.66	Botswana	0.93
Australia	0.72	U.K.	0.78	Austria	0.66	Canada	0.68	Saudi Arabia	0.19	South Africa	0.93
Spain	0.71	U.S.	0.65	Spain	0.66	Chile	0.66	Italy	0.08	Bolivia	0.93
U.S.	0.70	Chile	0.60	U.K.	0.66	Germany	0.66	China	0.05	France	0.92
Belgium	0.67	Belgium	0.59	U.S.	0.64	Belgium	0.63	Austria	0.04	India	0.92
France	0.66	France	0.56	France	0.62	Spain	0.59	Japan	0.03	Italy	0.92
Japan	0.55	Spain	0.52	Slovenia	0.59	Israel	0.56	India	0.03	Japan	0.92
Chile	0.52	Japan	0.49	Hungary	0.58	Hungary	0.55	Israel	0.03	Taiwan (China)	0.92
Israel	0.52	Israel	0.44	Italy	0.57	Taiwan (China)	0.54	Colombia	0.02	Spain	0.92
Malaysia	0.47	Slovenia	0.42	Poland	0.57	France	0.52	Indonesia	0.01	Peru	0.92
Taiwan (China)	0.44	Taiwan (China)	0.32	Japan	0.55	Japan	0.49	Viet Nam	0.01	Poland	0.92
Slovenia	0.43	Botswana	0.31	Chile	0.51	Italy	0.49	Venezuela	0.00	Belgium	0.92
Hungary	0.40	Hungary	0.28	Taiwan (China)	0.49	Poland	0.47	France	0.00	Mauritius	0.92
ROK	0.34	Mauritius	0.28	Mauritius	0.49	Slovenia	0.46	Botswana	0.00	Australia	0.92
Italy	0.34	South Africa	0.27	South Africa	0.46	Botswana	0.41	Malaysia	0.00	Ghana	0.92
South Africa	0.31	Poland	0.25	Botswana	0.44	ROK	0.40	Mauritius	0.00	Israel	0.92
Poland	0.30	Italy	0.25	Israel	0.44	Malaysia	0.39	Morocco	0.00	Austria	0.92
Botswana	0.27	Malaysia	0.24	ROK	0.42	Mauritius	0.38	Turkey	0.00	Slovenia	0.92
Mauritius	0.23	ROK	0.23	Brazil	0.37	South Africa	0.37	Spain	0.00	New Zealand	0.92
Mexico	0.19	Morocco	0.15	India	0.33	Peru	0.35	Kenya	0.00	Canada	0.92
Turkey	0.16	Brazil	0.15	Argentina	0.31	Mexico	0.33	South Africa	0.00	Hungary	0.92
China	0.15	Madagascar	0.15	Mexico	0.26	Turkey	0.32	Argentina	0.00	Switzerland	0.92
Argentina	0.15	Saudi Arabia	0.15	Philippines	0.24	Uganda	0.30	Bolivia	0.00	U.K.	0.92
Colombia	0.14	Colombia	0.14	Bolivia	0.22	Colombia	0.29	Malawi	0.00	Brazil	0.92
Philippines	0.14	Turkey	0.13	Mozambique	0.18	Saudi Arabia	0.29	Pakistan	0.00	U.S.	0.92
India	0.14	Ghana	0.13	Madagascar	0.18	Brazil	0.28	Brazil	0.00	Germany	0.92
Brazil	0.13	Mexico	0.13	Malawi	0.17	Philippines	0.26	Philippines	0.00	Burkina Faso	0.92
Ghana	0.12	Peru	0.11	Colombia	0.16	Burkina Faso	0.22	Zimbabwe	0.00	Mexico	0.92
Indonesia	0.11	Mozambique	0.11	Turkey	0.15	Indonesia	0.21	Taiwan (China)	0.00	Kenya	0.92
Viet Nam	0.09	Venezuela	0.10	Indonesia	0.14	China	0.21	Madagascar	0.00	Venezuela	0.92
Mozambique	0.09	Philippines	0.10	Burkina Faso	0.13	Malawi	0.20	Russia	0.00	Kyrgyzstan	0.91
Kazakhstan	0.09	Burkina Faso	0.10	Kenya	0.12	Kazakhstan	0.20	Mexico	0.00	Angola	0.89
Malawi	0.09	Indonesia	0.09	Russia	0.11	India	0.19	Poland	0.00	Chile	0.88
Pakistan	0.09	Viet Nam	0.08	Morocco	0.10	Russia	0.19	Hungary	0.00	Zimbabwe	0.88
Venezuela	0.08	Bolivia	0.08	Nigeria	0.09	Bolivia	0.19	Slovenia	0.00	Uganda	0.86
Bolivia	0.08	Pakistan	0.08	Pakistan	0.06	Madagascar	0.19	Mozambique	0.00	Madagascar	0.86
Kyrgyzstan	0.07	Ethiopia	0.07	Uganda	0.05	Kyrgyzstan	0.17	Ghana	0.00	Nigeria	0.83
Madagascar	0.07	Kazakhstan	0.07	Kazakhstan	0.05	Pakistan	0.16	Kazakhstan	0.00	Pakistan	0.82
Uganda	0.06	Russia	0.06	Chad	0.05	Venezuela	0.15	Nigeria	0.00	Philippines	0.80
Burkina Faso	0.06	Uganda	0.06	Zimbabwe	0.04	Viet Nam	0.15	Peru	0.00	Mozambique	0.79
Ethiopia	0.05	Kyrgyzstan	0.06	Ethiopia	0.04	Nigeria	0.12	Chad	0.00	Kazakhstan	0.76
Zimbabwe	0.04	Chad	0.05	China	0.03	Chad	0.12	Kyrgyzstan	0.00	Malawi	0.64
Chad	0.04	Zimbabwe	0.05	Viet Nam	0.03	Ethiopia	0.10	Uganda	0.00	Indonesia	0.62
Angola	0.02	Congo	0.04	Angola	0.02	Zimbabwe	0.06	Angola	0.00	Chad	0.58

Notes: This table lists the ranks of countries' disaster relief efficiencies using all the institutional variables in this study. Ranks are aquired using the stochastic frontier model. The efficiency value for each country is the yearly average over 1996 to 2010.

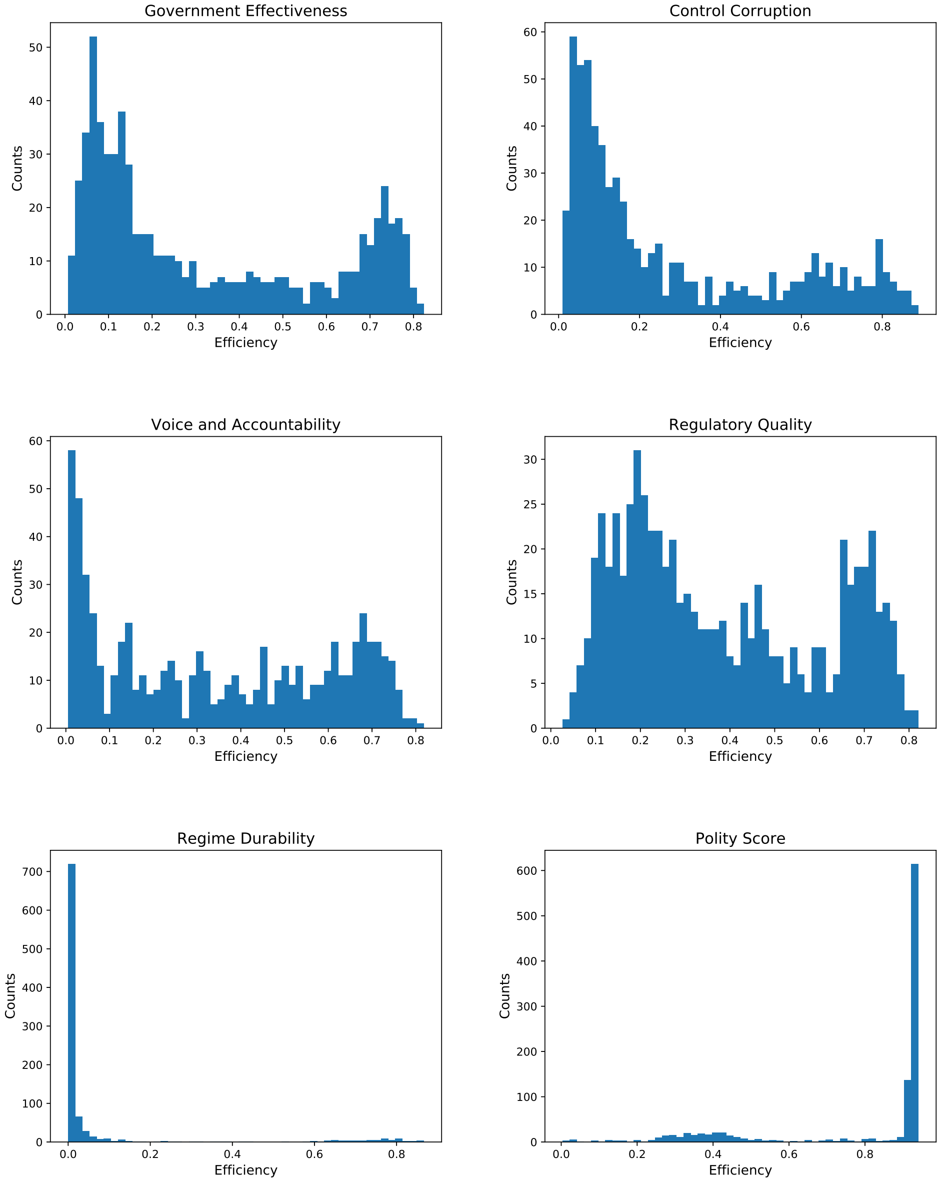

Figure 3: Distribution of Efficiencies. We plot histograms for disaster relief efficiency (maximum score is 1). We estimate a stochastic frontier model where the inefficiency term u follows a truncated normal distribution. Crucially, we let the institutional variable determine both the truncation point and the variance. Each set of efficiency values is based on an estimation with one of the six institutional variables, i.e. government effectiveness, control of corruption, voice and accountability, regulatory quality, regime durability, and polity score.

of corruption, regime durability, voice and accountability, and regulatory quality. Meanwhile, our estimates also show that institutional quality has no impact on reducing the volatility of efficiencies. None of the estimated ψ's are significant.

To quantify the relationship between institutions and efficiencies, we draw a scatter plot of institutional quality values and the calculated efficiencies for each regression in Figure 4. We find a significant economic effect of institutions on efficiency. Referring to summary statistics in Table 1, a one standard deviation in the government effectiveness corresponds to a 20% to 29% efficiency change, while a one standard deviation in the control of corruption score indicates a 24% to 33% efficiency change. We observe the same pattern for institutional quality variables like voice and accountability and regulatory quality. Furthermore, the slope of each of the plotted curves becomes steeper as the scores increase: the effects of governance quality are even more pronounced for countries that already have good quality institutions.[14] The last two sub-figures in Figure 3 show that there is little variance in disaster relief efficiency to explain when it comes to regime durability and the polity score.

Finally, considering that our analysis has controlled for a large set of "hardware" variables including country fixed effects, it is worth noting that the estimated changes in efficiency mainly reflect variations in institutional quality over time. Therefore, the evidence in Figure 4 contains a strong message to countries about the need to reform institutions if they want - and need - to improve how they handle natural hazards. This message gains urgency when the incidence and intensity of natural hazards tends to rise with climate change and increases in population, capital, and economic activity located in hazard prone areas.

4.4. From Efficiencies to Real Damages

Our analysis is motivated by the enormous impact natural hazards can have on people and capital. Subsequently, we have analyzed the role of institutions as ways to mitigate that impact. Now it is time to close the loop, and ask what an improvement in disaster relief efficiency would really imply for local economies and people? We therefore complete our reasoning by translating improvements in efficiency back to 'real' variables, i.e., the number of people killed, affected, and economic damages.

Figure 5 displays scatter plots to show the relationship between efficiency and the consequences of disasters. Results are based on regressions using government effectiveness, control of corruption, voice and accountability, and regulatory quality as these have proven most informative in explaining efficiency differences. We find a significant negative relationship between efficiency levels and the number of people killed (affected) and a significant positive relationship between efficiency and material damages. On average, a 10% efficiency increase implies a 0.25% (0.3%) drop in the number of people killed (affected) and a 0.7% increase in material damages. Taking our sample averages of disasters as an admittedly very crude measure, this implies that a country with a 10% higher

[14] It is important to note that from a technical point of view, this fast increasing curve is expected by construction. Looking at equations 12 and 11, the effect of the institutional variable on efficiency is $\frac{\mathrm{d}e_{j,i,t}}{\mathrm{d}z_{j,i,t}} = \frac{\mathrm{d}e_{j,i,t}}{\mathrm{d}u_{j,i,t}}\frac{\mathrm{d}u_{j,i,t}}{\mathrm{d}z_{j,i,t}} = -\exp(-u_{j,i,t})\eta$. As inefficiency decreases from large values towards zero, the exponential term increases even faster. In short, the rapidly increasing curve is mainly caused by transforming from inefficiency to efficiency using $e_{j,i,t} = \exp(-u_{j,i,t})$.

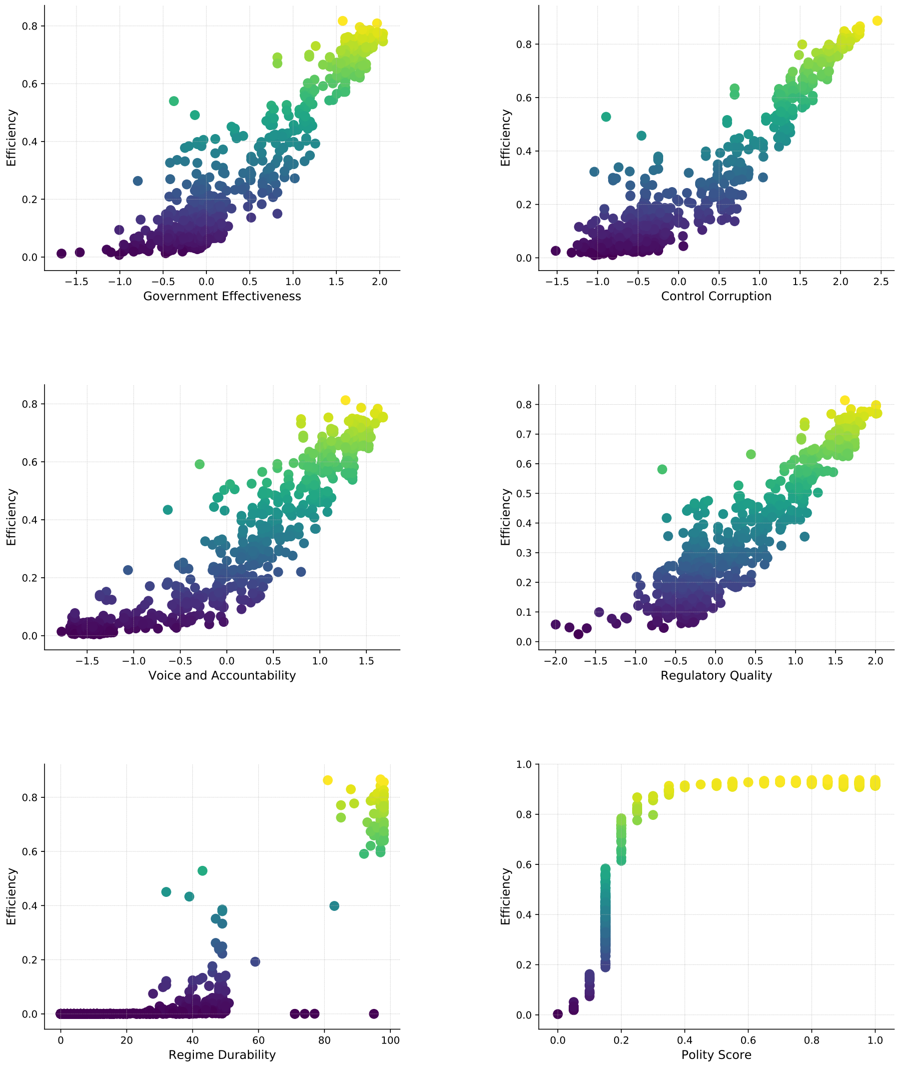

Figure 4: Disaster Relief Efficiency and Institutional Variables. This figure shows the scatter plots of the relationship between our institutional variables and the disaster relief efficiency estimated by the stochastic output distance model. The plots show a significant positive relationship between disaster relief efficiency and our institutional quality measures, e.g. government effectiveness, control of corruption, regime durability, voice and accountability.

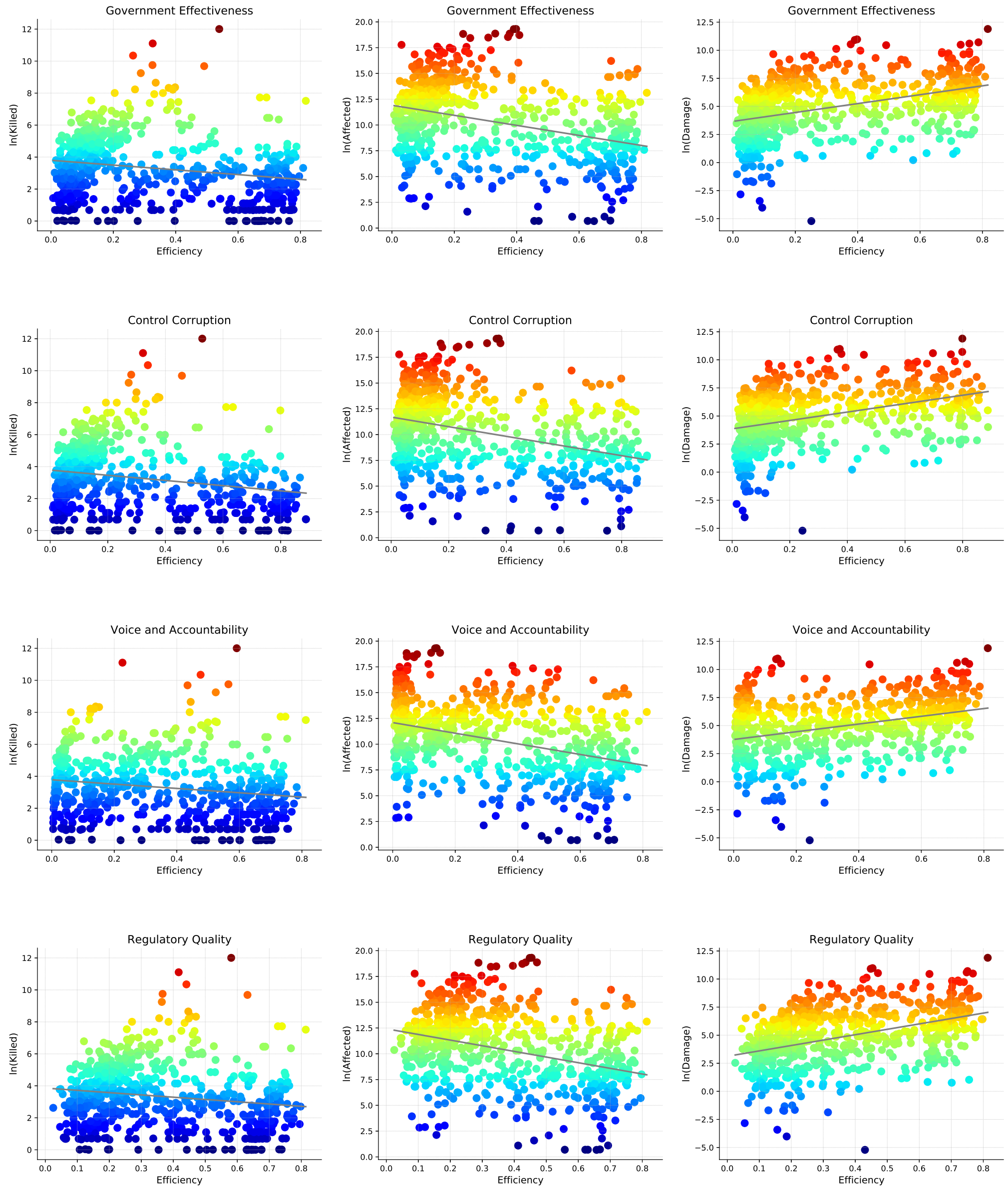

Figure 5: Disaster Relief Efficiency and Cost Variables. This figure shows scatter plots of the relationship between efficiency and disaster consequences (number of people killed, number of people affected, and damage in millions of dollars, all in log).

disaster relief efficiency can save one more life and protect four more people at the cost of $8 million.

As countries improve their governance quality and disaster-relief capacity, they emphasize preventing human losses and will suffer more material damages as a consequence, resulting in a trade-off between saving people's lives and reducing material damages.[15]

5. Conclusion

It is a long known fact that building and maintaining high quality institutions is crucial for long-term growth. In this paper we show that those same institutions also play an important role in short-term resilience to natural hazards shocks. After constructing and analyzing a comprehensive data set that provides us with hazard intensities and different measures of damage, we introduce a model that helps us to evaluate and rank countries' disaster relief efficiency. The same model also allows us to explore in more detail how institutional variables contribute to a higher level of efficiency.

We show that countries differ a lot in their disaster relief efficiencies, with richer countries performing better than poorer countries. We also show richer countries incur higher capital losses in exchange for fewer lives affected. Countries with institutions of higher quality indeed have higher disaster relief efficiencies. Most important are indicators of good governance, whereas the de jure indicator is not informative. In real terms, taking our sample disaster averages as a crude measure, a country with a 10% higher disaster relief efficiency can save one more life and protect four more people at the cost of $8 million in capital losses.

[15]Note that both the killed and affected numbers are not scaled by the material damage as we did in the model. After scaling the two variables, the negative relationship becomes stronger as can be seen from Figure .7 in Appendix 5. This shows that the relationships are robust.

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Appendix A

To reveal the relationships among our development levels and institutional measures, we present the table and heat map for the correlation matrix in Table .4 and Figure .6. The illustrations show that any one development level indicator (except for population) is usually positively related to other measures for development as well as institutional quality. One important message here is perhaps that the polity score is positively correlated with other institutional measures and the values are similar to those of others. This excludes the possibility that the insignificant contribution of polity score on efficiency found in later sections is due to low correlation.

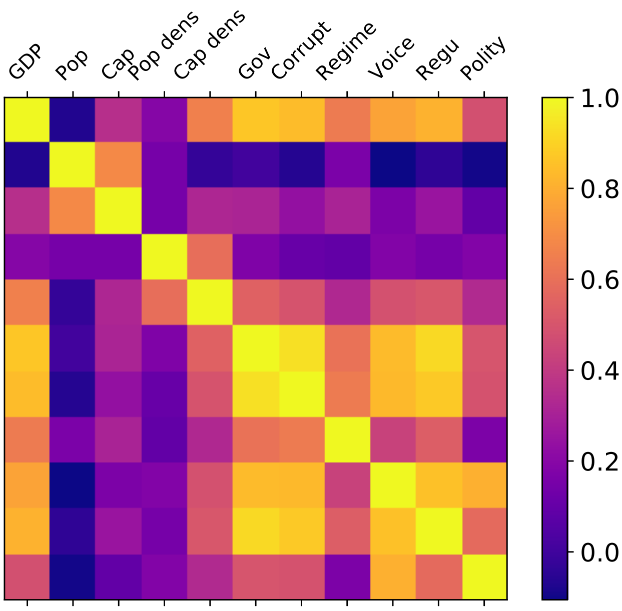

Figure .6: Correlation Matrix. This figure is a visualization of the correlation matrix in Table .4.

Appendix B

Table .4: Correlation Matrix of the Development Indicators and Indicates of Institutional Quality

GDP per capita	Population	Capital stock	Population density	Capital density	Government effectiveness	Control corruption	Regime durability	Voice and accountability	Regulatory quality	Polity score
1.000	-0.067	0.358	0.194	0.657	0.866	0.843	0.638	0.767	0.812	0.485
-0.067	1.000	0.687	0.152	-0.023	0.009	-0.061	0.166	-0.105	-0.037	-0.096
0.358	0.687	1.000	0.150	0.322	0.316	0.236	0.310	0.170	0.253	0.094
0.194	0.152	0.150	1.000	0.596	0.178	0.109	0.094	0.188	0.150	0.188
0.657	-0.023	0.322	0.596	1.000	0.550	0.498	0.331	0.490	0.511	0.339
0.866	0.009	0.316	0.178	0.550	1.000	0.938	0.610	0.838	0.921	0.499
0.843	-0.061	0.236	0.109	0.498	0.938	1.000	0.637	0.833	0.879	0.492
0.638	0.166	0.310	0.094	0.331	0.610	0.637	1.000	0.434	0.536	0.167
0.767	-0.105	0.170	0.188	0.490	0.838	0.833	0.434	1.000	0.857	0.808
0.812	-0.037	0.253	0.150	0.511	0.921	0.879	0.536	0.857	1.000	0.579
0.485	-0.096	0.094	0.188	0.339	0.499	0.492	0.167	0.808	0.579	1.000

Notes: This table reports the correlation matrix of variables including the development indicators and indicates of institutional quality. Each value is the yearly average correlation over 1996 to 2010.

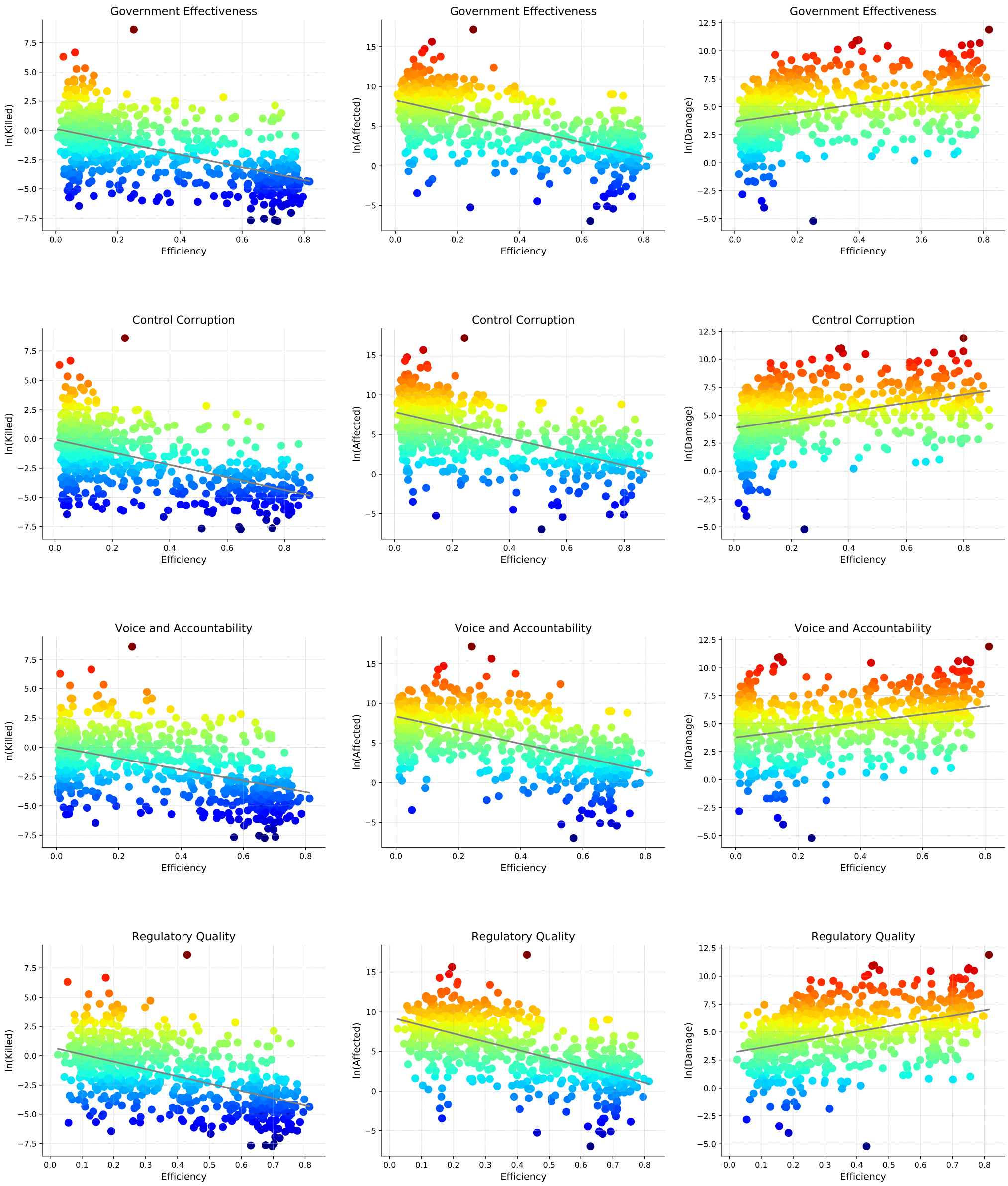

Figure .7: Disaster Relief Efficiency and Cost Variables. This figure shows the scatter plots of the relationship between efficiency and disaster consequences (number of people killed/damage, number of people affected/damage, and damage, all in log form).