Natural disasters: the impact of collective and sudden events on preferences for redistribution Online Appendix

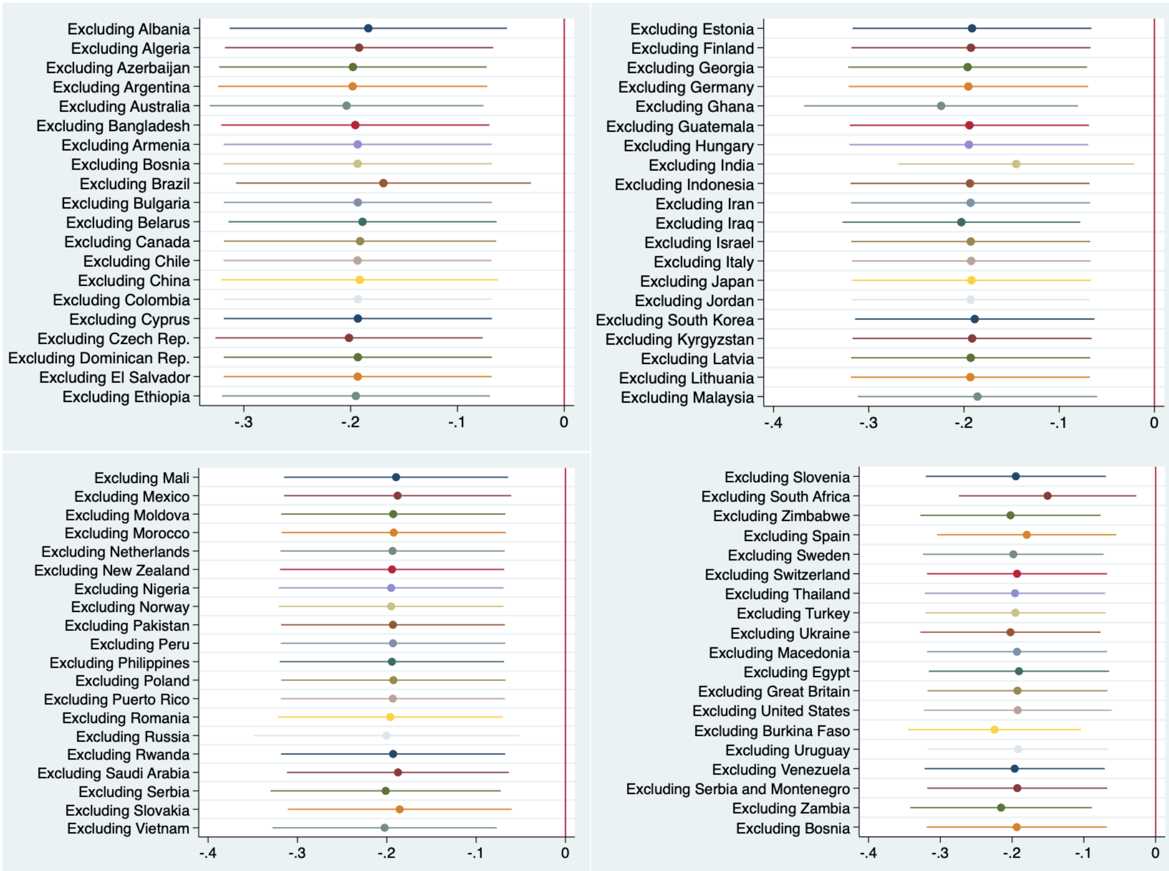
Contents

A Summary statistics

Table A1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Redistribution	240,152	5.191724	2.99449	1	10
Dist(eq_34)	251,240	0.4833769	0.6332229	0	3.319654
Age	257,007	40.99629	16.27236	13	99
Age sq	257,007	1945.484	1500.025	169	9801
Male	255,416	0.4681774	0.4989873	0	1
Married	257,426	0.5675301	0.4954197	0	1
Unemployed	257,426	0.0909543	0.2875447	0	1
Abs latitude	251,240	32.97146	14.58118	0.1194381	67.66924
Dist(coast)	251,240	0.2546978	0.2818552	0	1.989509
quake	251,240	0.067334	0.2506001	0	1
quake_1	251,240	0.0767155	0.26614	0	1
Hard work	196,090	6.782457	2.833635	1	10
Risk loving	70,525	5.081149	2.944442	1	10
Open new ideas	89,688	5.24845	2.933398	1	10
Welcome changes	15,675	6.211738	2.95973	1	10
Trust gov	227,170	2.403108	0.9328672	1	4
Educ	226,905	4.708658	2.237758	1	8
Lights2000	249,774	9.57018	12.87824	0.00821	62.9814
Area(1000km2)	251,240	0.1359466	0.3037529	3.55E-11	2.997855
Year	251,240	2002.846	7.233917	1981	2014

B Main results in Table 2 excluding one country at a time



C Characteristics of populations in high and low earthquake risk areas

Figure 1: Balance test, entire sample

VARIABLES	(1) Distance to earthq zones 3-4
Age	0.000
	(0.000)
Agesq	-0.000
	(0.000)
Male	-0.007***
	(0.002)
Married	-0.006**
	(0.003)
unemployed	0.007
	(0.006)
Income level (deciles)	0.000
	(0.001)
Education	-0.000
	(0.001)
Absolute latitude	-0.008*
	(0.005)
Dist(coast), 1000km	-0.219*
	(0.118)
Night lights per km2	-0.808
	(1.145)
Observations	200,968
R-squared	0.860
Regions	762
Countries	77

Figure 2: Balance test including GINI coefficient at the subnational level, OECD subsample

VARIABLES	(1) Distance to earthq zones 3-4
Age	0.000
	(0.000)
Agesq	0.000
	(0.000)
Male	-0.002
	(0.002)
Married	0.001
	(0.003)
Unemployed	0.002
	(0.003)
Income level (deciles)	-0.000
	(0.001)
Education	0.001
	(0.001)
Gini coefficient (subnational, aftertax)	-0.910
	(0.824)
Absolute latitude	0.011
	(0.008)
Dist(coast), 1000km	-0.007
	(0.161)
Night lights per km2	429.086
	(401.756)
Observations	54,882
R-squared	0.922
Regions	184
Countries	24

D Individual level results, only democracies

VARIABLES	(1) Income equality	(2) Income equality	(3) Income equality
Distance to earthquake zones 3-4	-0.295***	-0.294***	-0.699***
	(0.085)	(0.087)	(0.178)
Dist(earthq) squared			0.173***
			(0.057)
Observations	131,473	120,733	131,473
R-squared	0.126	0.136	0.126
Baseline controls	Y	Y	
Outcome measure	incomesequal	incomesequal	
Regions	457	446	457
Countries	51	51	51
Impact at 500 km			-0.613

Standard errors in parentheses, clustered at the first administrative division level. All specifications include country-by-year fixed effects and control for individual characteristics. Model (1) shows baseline results. Model (2) controls for level of education and district level development. Model (3) adds squared distance to high intensity earthquake zones (to allow for a non-linear effect of distance). ***p<0.01, **p<0.05, *p<0.1

E Matching WVS data to earthquake data

In her compilation, Bentzen (2019) linked earthquake zones to a shapefile containing all subnational districts across the world and used GIS software to create a variable measuring distance from a subnational district's border to the closest high intensity earthquake zone. She classified high intensity as intensity zones 3 and 4. I used her publicly available replication files to obtain this measure of distance to high intensity earthquake zone for each sub-national district in the WVS dataset.

The process of linking this variable at the sub-national level to the pooled World Values Survey (WVS 1981-2014) was at times manual, since the names and categories referring to sub-national district in her dataset were not exactly the same to that in the World Values Survey data. The reason for this was that the variable X048 (capturing location of interview) in the World Values Survey is sometimes not consistent across waves within the same country. Bentzen (2019)'s linked dataset was thus the result of a process of going through the sub-national district names and homogenizing the sub-national district categories of the same country across the waves. Then, she edited a shapefile[1] of all first administrative divisions worldwide (available here: https://gadm.org/) to resemble the chosen divisions as close as possible. The sub-national divisions in WVS and those in the publicly available shapefile did not match perfectly either because for some countries, the WVS variable captures the first administrative divisions in the country (first level of disaggregation) but in other cases the variable refers to cities. The shapefile is necessary in this process because it is the file that allows to use GIS software to calculate distances, the way the independent variable of the individual level analysis was constructed.

For the event study, I used the already calculated variables from Bentzen (2019). In her replication files, she has calculated a dummy capturing whether one or more earthquakes hit a given district between WVS waves and the number of earthquakes that hit the district between waves for each sub-national district in WVS for which there was more than one measurement (countries with more than one WVS wave). These variables were calculated in a rather complex and technical process. First, the earthquake database from Advanced National Seismic System (ANSS) is organized at the grid-cell level. In order to create the two variables capturing earthquake *incidence*, Bentzen (2019) followed similar process as the one described above to match the categories of sub-national districts present in the World Values Survey and those in the first administative division shapefile. The latter was edited to match the divisions in the WVS. The earthquake database was linked to the shapefile using longitude and latitude information. GIS software was used to create a buffer of 100km around the border of each subnational district and to identify which of those buffers were hit by the epicenter of an earthquake in a given year. This information was then used to create the two final variables of a dummy capturing whether an earthquake hit between waves and the number of earthquakes that hit.

[1] A shapefile is a type of file that contains geographic information and is intended to be used with some geographic information system (GIS) software that allows to map the information.

F Data on other disaster types

The data for alternative disasters originally come from and are publicly available at various sources. The dataset of tsunami events comes from the "Global Historical Tsunami Events and Runups" database from the National Geo-physical Data Center NOAA (2018) (available at https://www.ngdc.noaa.gov/hazard/tsu.shtml). From this raw data, I used GIS techniques to calculate the geodesic distance from the centroid of each sub-national district to the nearest tsunami ever recorded.

Tropical storm risk data is based on a map of tropical storm intensity zones derived from the Munich Reinsurance Company's (Munich Re) World Map of Natural Hazards Munich (1998). The intensity zones are calculated on the probability that a storm falls within five different speed categories on the Saffir-Simpson Hurricane Scale. The categories are the following:

1. 119-153 km/h: Very dangerous winds will produce some damage.
2. 154-177 km/h: Extremely dangerous winds will cause extensive damage.
3. 178-208 km/h: Devastating damage will occur.
4. 209-251 km/h: Catastrophic damage will occur.
5. 252 km/h or higher: Catastrophic damage will occur.

Finally, data on volcanic risk is based on volcanic eruption intensity zones. Original data come from a database of 1420 volcanic eruptions that span approximately the last 10,000 years Global Volcanism Program (2013) and transformed into volcanic eruption intensity zones and made readily available by Siebert et al. (2011); Bentzen (2019). Each eruption is spread over a radius of 100km around the eruption to define areas likely to be affected by it. The 'intensity' is measured via the the density of volcanic eruptions. To this end, the 0 to 6 Volcanic Explosivity Index (VEI), devised by Chris Newhall and Stephen Self, is used to rate volcanic eruptions. The index takes into account the explosivity and time period of the eruption. The key variable capturing exposure to volcanic risk measures geodesic distance of a sub-national district to the closest volcanic intensity zone 2 or above.

G Correlations between risk of different disaster types

Correlations between the different disaster risk measures

	dist(quake zones)	dist(tsunamis)	dist(storm risk zones)	dist(volcanic risk zones)
dist(quake zones)	1			
dist(tsunamis)	0.3594	1		
dist(storm risk zones)	0.2192	-0.0181	1	
dist(volcanic risk zones)	0.3543	0.5209	-0.0713	1

H Heterogeneus impact by income decile

Table 1

VARIABLES	(1) Incomes should be made more equal (1-10)
Distance to earthquake zones 3-4	-0.311***
	[0.087]
Income_decile2 * dist(quakezones3-4)	0.075
	[0.083]
Income_decile3 * dist(quakezones3-4)	0.055
	[0.071]
Income_decile4 * dist(quakezones3-4)	0.018
	[0.076]
Income_decile5 * dist(quakezones3-4)	0.112
	[0.086]
Income_decile6 * dist(quakezones3-4)	0.117
	[0.083]
Income_decile7 * dist(quakezones3-4)	0.179*
	[0.092]
Income_decile8 * dist(quakezones3-4)	0.194**
	[0.095]
Income_decile9 * dist(quakezones3-4)	0.212**
	[0.102]
Income_decile10 * dist(quakezones3-4)	0.238**
	[0.118]
Observations	193,743
R-squared	0.157
Baseline controls	Y
Regions	740
Countries	77

Standard errors in brackets, clustered at the first administrative division level. The interaction terms allow for the effect of the distance to earthquake zones 3 and 4 to vary by different income levels. Controls include dummies for all income decile levels, individual characteristics (age, age squared, sex, marital status, whether unemployed), and sub-national district geographical and developmental characteristics (latitude, distance to the coast, whether an earthquake occurred in that year or a year before, and night lights per squared in 2000). *** p<0.01, ** p<0.05, * p<0.1

I Other alternative explanations: risk attitudes and respect for tradition

There may be alternative mechanisms through which natural disasters affect attitudes toward inequality other than through the aforementioned psychological and relational channels. To investigate these concerns, I repeat the same empirical strategy of the individual level analysis but substituting the redistribution outcome for other traits that the literature has found to correlate with demand for redistribution and report the results in Table 2.

Risk attitudes. Are individuals more in favor of redistribution after a natural disaster due to changes in risk aversion? Individuals who are exposed to a natural disaster may update their beliefs about the riskiness of the environment which could alter their decision to demand more or less social insurance from the state against potential future shocks. This reasoning is in line with findings that economic shocks influence attitudes toward inequality through changes in risk attitudes (Rehm, 2009; Cusack et al., 2006; Moene and Wallerstein, 2001; Iversen and Soskice, 2001). More recently, (Pahontu, 2020) has found individuals nearly missed by hurricanes also shift their risk attitudes and this in turn influences the political party they support. Nevertheless, as reported in my investigation of alternative mechanisms shown in Table 2, there is no evidence here that natural disasters lead to changes in risk attitudes and thus these are unlikely to account for my main results. The lack of a correlation between disasters and risk attitudes could be due to several factors. For instance, different cultures may dictate different consequences of a disaster on risk attitudes. Secondly, the literature on how natural disasters may impact risk aversion is inconclusive[2]. Finally, it is not obvious that the null result is a measurement problem[3]. Indeed, recent work suggests survey measures of risk attitudes outperform measures taken through controlled choices between monetary lotteries Charness et al. (2013); Hertwig et al. (2019); Arslan et al. (2020)[4].

Trust. Single country studies have found that natural disasters may affect both generalized trust and trust in government, albeit evidence on the direction of the relationship is mixed (Cassar et al., 2017; Toya and Skidmore, 2014; Ahsan, 2014; Dussaillant and Guzmán, 2014). Generalized trust and trust in government have in turn been linked to preferences for redistribution, even though evidence for this connection is also mixed (Peyton, 2020). As shown in Table 2, I find no evidence that exposure to disasters affects trust in government[5].

Respect for tradition. According to evolutionary anthropological theories of social learning, individuals in unstable environments are less likely to copy from earlier generations and more likely to come up with solutions to problems on their own (Richardson and Boyd, 1985; Rogers, 1988; Feldman et al., 1996; Aoki and Feldman, 1987). In more stable environments, the theory goes, the benefits of social learning are higher and thus individuals are more likely to stick to the solutions offered by previous generations and show higher respect for tradition. In a worldwide test of this hypothesis using global temperature data and the World Values Survey, Giuliano and Nunn (2017) find evidence in support of it. Perhaps being close to disaster risk zones also makes individuals less likely to respect

[2]Some studies find natural disasters make individuals more risk loving (Eckel et al., 2009; Hanaoka et al., 2018; Page et al., 2014; Bchir et al., 2013) while others find the opposite (Van Den Berg et al., 2009; Reynaud and Aubert, 2014; Cameron and Shah, 2015; Cassar et al., 2017).

[3]Here, risk attitudes are measured through a World Values Survey question that asks respondents to what extent the following statement describes you: *"It is important to this person: adventure and taking risks"*. Possible answers range from 1 (Very much like me) to 5 (Not at all like me). This same question has been used to measure risk attitudes in recent work (e.g. Bénabou et al. (2015)).

[4]As a possible explanation for this, some suggest that "the fairly vague, almost projective nature of a comprehensive single-item question allows people to refer back to their diagnostic memories and behaviours using a well-honed human capacity for social perception" (Arslan et al., 2020, p.10).

[5]Results are also insignificant for generalized trust, these are available upon request.

tradition, loosen their kinship ties[6], and more likely to turn to the state for help. To investigate this possibility, I employ the same question from the World Values Survey used by Giuliano and Nunn (2017) in their study of respect for tradition and unstable environments. As shown in Table 2, there is no evidence that proximity to high intensity earthquake zones affects respect for tradition.

Table 2

VARIABLES	(1) Hard work	(2) Risk loving	(3) Open New ideas	(4) Life satisfaction	(5) Trust gov	(6) Tradition
Distance to earthq zones 3-4	0.151*	0.039	0.293*	0.134*	0.048	0.01
	[0.082]	[0.167]	[0.164]	[0.073]	[0.037]	[0.042]
Observations	171,535	57,536	74,437	214,189	200,287	109,490
R-squared	0.112	0.09	0.139	0.213	0.179	0.198
Baseline controls	Y	Y	Y	Y	Y	Y
Regions	690	307	349	740	715	544
Countries	76	48	51	77	76	64

To construct these results, I employ the same empirical strategy as in Table 1, Panel C but changing the outcomes to a series of variables capturing different mechanisms from Figure 2 (belief in hard work, decreased respect for tradition, trust in government, and risk attitudes). Standard errors in brackets, clustered at the first administrative division level. *** p<0.01, ** p<0.05, * p<0.1

[6]See Alesina and Giuliano (2014) for a discussion of how weaker kinship or family ties are associated with higher preference for redistribution.

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