1 Supplemental Online Appendix

1.1 Summary statistics by risk category

Table 1: Summary Statistics by risk category

	Full Sample	Risk = 1 *Most Risky*	Risk = 2 →	Risk = 3	Risk = 4 *Least Risky* →	Risk = GA *Gamble Averse*
Male	0.46	0.57	0.51	0.53	0.47	0.40
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
Age	35.36	34.73	33.52	32.33	33.87	36.31
	(13.54)	(12.53)	(12.92)	(12.67)	(12.91)	(13.99)
Married	0.73	0.74	0.69	0.65	0.72	0.75
	(0.44)	(0.44)	(0.46)	(0.48)	(0.45)	(0.43)
Urban	0.51	0.52	0.56	0.55	0.57	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Javanese	0.43	0.36	0.41	0.44	0.47	0.45
	(0.49)	(0.48)	(0.49)	(0.50)	(0.50)	(0.50)
Sundanese	0.12	0.11	0.12	0.08	0.13	0.11
	(0.32)	(0.32)	(0.33)	(0.27)	(0.33)	(0.31)
Years of Schooling	8.28	9.15	9.32	9.84	9.16	7.59
	(4.48)	(4.51)	(4.46)	(4.14)	(4.34)	(4.40)
Muslim	0.90	0.90	0.89	0.88	0.89	0.89
	(0.30)	(0.30)	(0.31)	(0.32)	(0.31)	(0.31)
5 Yr Disaster Mortality Rate	0.16	0.14	0.14	0.09	0.21	0.15
	(0.77)	(0.71)	(0.71)	(0.50)	(0.90)	(0.77)
Observations	21,137	2,330	1,259	922	4,479	8,786

Note: Standard Deviation in parentheses. Summary statistics measured in wave 4, and only include those who have risk data in wave 4 and wave 5. Disaster mortality rate is adjusted for district population per 1,000 residents.

1.2 Alternative Disaster Measurements

EM-DAT, the international database for disasters, reports deaths economic damages for disaster events across the globe.[1] Accuracy of economic damages from natural disasters relies on the reporting capabilities of the government and is inconsistent across different countries. As Indonesia has focused efforts on disaster management since the 2004 Tsunami, damages are likely more accurate than other developing countries. However, EM-DAT data reports the damages from each disaster event and lists affected districts, but does not report damages per district (i.e., the statistics are less geographically accurate) and may be less reliable than the BPNB database.[2] I run the analysis in two ways: (1) each district listed is assigned the full impact of the disaster event (inherently an overestimation), and (2) assuming each district affected equally, and dividing the damages among the affected districts.

When I run equation [2] using the deaths from EM-DAT instead of the BNPB, the results hold in sign and generally in statistical significance, although the coefficients are

[1] As mentioned earlier, EM-DAT tracks events that have killed 10 or more people or have affected 100 or more people

[2] Additionally, some disasters only have province information or are missing geographic location altogether. In these instances, I use secondary sources to corroborate specific districts that were affected.

Table 2: *EMDAT Data*: Deaths and Damages Effect on Risk Category

	Mortality Rate		**Damages**	
	Total	Split	Total	Split
	(1)	(2)	(3)	(4)
1 Year	0.200	0.935	0.010	0.187
	(0.147)	(0.144)	(0.011)	(0.180)
District Mean	*0.02*	*0.001*	*0.11*	*0.01*
District Max	*1.97*	*0.16*	*20.20*	*1.22*
5 Years	0.013*	0.131*	0.016	0.105
	(0.007)	(0.067)	(0.011)	(0.105)
District Mean	*0.66*	*0.07*	*0.51*	*0.06*
District Max	*19.49*	*2.73*	*23.57*	*1.56*
10 Years	0.002	0.033	-0.003	-0.035
	(0.008)	(0.098)	(0.006)	(0.113)
District Mean	*1.55*	*0.15*	*1.34*	*0.12*
District Max	*100.53*	*10.23*	*53.31*	*5.28*
15 Years	0.000	-0.040	-0.001	-0.058
	(0.010)	(0.118)	(0.001)	(0.045)
District Mean	*1.61*	*0.16*	*2.74*	*0.17*
District Max	*100.53*	*10.23*	*174.48*	*5.85*

Notes: N=15,894 (7,947 IFLS respondents). Robust standard errors in parentheses, clustered at the district level. Each coefficient shown in table is from a separate regression with individual and wave fixed effects. Mortality rate is per 1,000 residents in a district, damages are measured in millions of US dollars and also adjusted for population (per 1,000 residents). EM-DAT reports statistics at the disaster level, and lists affected districts, not district-specific statistics. Therefore Columns (1) and (3) show the effect when the total disaster impact is assigned to each affected district, and Columns (2) and (4) show the effects when the disaster impact is split equally among the affected districts. District mean and max shows the average and maximum, respectively, for each time frame and disaster measurement to give context for the coefficient magnitude. Number of observations, respondents, and the adjusted R-squared are the same for every regression in each column. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

smaller, likely due to the measurement error associated with the disaster locations. The results of the EM-DAT regressions can be found in Table 2 above. When I use economic damages as the D_{jt} measure, damages (population adjusted) have no significant impact and the coefficient is relatively small. Results are statistically significant at the 10% level for the five-year time frame, and then fades at the 10 year time frame.[3] These results are notable for two reasons. First, results from the EM-DAT analysis are consistent with the findings using the BPNB data, showing that the main results hold regardless of which database for disasters is used. Second, these results show that disaster mortality is more salient to individuals than economic damages, indicating the possibility of risk preference changes induced by high-mortality, rather than financial costs of disaster. This may perhaps be due to a psychological component of high-mortality events that are traumatic enough to change an individual's underlying attitude toward risk.

Table 3: Risk Category on Total Houses Destroyed in District from All Disasters
adjusted for district population (per 1,000)

	Risk Category		
	(1)	(2)	(3)
Houses Destroyed Past 1 Year	-0.118***		
	(0.031)		
Houses Destroyed Past 5 Years		0.003***	
		(0.001)	
Houses Destroyed Past 9 Years			0.001
			(0.001)
Mean # Houses	0.13	2.37	4.45
Number of respondents	7,947	7,947	7,947
Observations	15,894	15,894	15,894
Adjusted R-squared	0.023	0.020	0.020

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects. Mean number of houses destroyed are per 1,000 people in district. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Additionally, the BNPB also reports other measures of disaster, including houses destroyed and evacuations, and I use these as alternative disaster severity measurements, see Tables 3 and 4. For houses destroyed, results for the 5 year time frame are similar in sign and significance, and while the coefficients are smaller in magnitude, this is because the number of houses destroyed in a disaster is typically higher than the mortality rate. When this is taken into account, the results closely mirror the main results. Houses destroyed in the district in the past year, however, has a negative impact on risk attitudes. This could be because there is a different psychological response in the short run causing people to become more risk loving when there is physical damage rather than human costs, or that in the short term the community support, temporary housing, or aid received counteracts the

[3]Results are significant at the 5% level for the six- to nine-year time frames.

impact on risk aversion. Because the BNBP only started tracking houses destroyed in 1999, I am only able to show results for houses destroyed up to 9 years, but a similar pattern to mortality appears over the 7-9 year time period, suggesting the effect fades faster than when measuring mortality.

Table 4: Risk Category on Total Evacuations in District from All Disasters
adjusted for district population (per 1,000)

	Risk Category			
	(1)	(2)	(3)	(4)
Evacuation Past 1 Year	-0.003*			
	(0.002)			
Evacuation Past 5 Years		0.0002		
		(0.0002)		
Evacuation Past 10 Years			-0.0003	
			(0.0004)	
Evacuation Past 15 Years				-0.0001
				(0.0003)
Mean # Evacuations	4.0	35.1	67.8	70.7
Number of respondents	7,947	7,947	7,947	7,947
Observations	15,894	15,894	15,894	15,894
Adjusted R-squared	0.02	0.02	0.02	0.02

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects. Mean Evacuations are per 1,000 people in district. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Evacuations also negatively impact risk attitudes after 1 year but have a smaller impact than destroyed houses and is only significant at the 10% level. Generally, when looking over time frames longer than one year, evacuations do not influence risk attitudes significantly. When evacuations are higher, or early warning systems work to evacuate people earlier, death may be avoided. Therefore, results indicate that being displaced to avoid disaster means that the disaster does not significantly impact risk attitudes. This may have implications for policy as it may be worth investing in technology that will allow governments to evacuate residents earlier and more efficiently to avoid disaster mortality.

1.3 Disasters as Fat-tailed Events

Conte and Kelly (submitted) explore the implications of disasters being fat-tailed events, where damages and mortality may not follow a normal distribution, and tail events may occur with higher frequency than expected. One property of these events is that the largest observations in the data are poor predictors for subsequent tail events. The fact that disasters are fat-tailed may be driving the change in risk perceptions which requires belief updating, since this would be unexpected if these losses were normally distributed. While Conte and Kelly (submitted) focuses on climate change specifically, they do also speculate on the implications for disaster management. They point out that large disaster events decrease property values in affected communities, cause an uptick in insurance policy purchases after major flooding, and can have important bankruptcy risk consequences as there may be an underestimation of damage from catastrophic events. Under such circumstances, tail event occurrences may increase the reserve requirements and could in turn increase insurance rates to cover the increase. This is exacerbated by some findings that these events likely have non-stationary distributions due to climate change (Coronese et al., 2019). Additionally, these events are unlikely to impact the population uniformly, and maybe affect low-income property owners who are less likely to be insured more than wealthier individuals. Policy makers must think about the welfare cost associated with tail events that cause large damages and high mortality, and are likely to impact those residents with lower wealth. For some suggestive evidence that disaster mortality and damages are likely fat-tailed events that require particular policy attention, see Figure 1 which shows Quantile-Quantile Plots.[4] This is especially important during a time when Indonesia is engaging the World Bank on disaster risk financing and insurance programs, as well as implementing Rice Farming Insurance programs to protect rice farmers in the face of increased flooding, typhoons, and other disasters. As can be seen in the figure, for both damages and deaths caused by disasters, the right tail lies above the normal distribution and log-normal distributions (the modeling used by the World Bank to determine estimates for future losses and the requirements for future public spending), indicating that disaster are fat-tailed events. While outside the scope of this paper, it would be beneficial to understand how alternative policies would be affected by fat-tailed events, especially as it pertains to belief updating and insurance pricing.

1.4 Time Preference

Risk preferences are closely tied to time preferences, or the amount of patience an individual displays. Several studies have found that there is a negative relationship between time and risk preferences. One way to corroborate the main results on risk preferences is examining the impact of disasters on time preferences. In additions to the risk preference questions, the IFLS also includes questions on time preference. The questions follow a similar structure to the games in the risk preference section, except individuals are given the option between an amount today or another amount one or five years from now. The specific questions can be found below in Table 5.

The results show a similar pattern to risk preference, but in the opposite direction. One might expect that if disasters are making people more risk averse, they would also make individuals more impatient due to the increase in uncertainty and weighing the present more heavily. However, I find that individuals are much more patient in the short run (deaths measured over the past year), are mildly more patient when analyzing disasters over three to nine years and in the longer term (10+ years) are more impatient, again suggesting a reversion back to the original time preference (although the long term results are insignificant). These results are summarized in Table 6 and Figure 2. The table shows the numerical results looking at snapshots for disasters measured over 1, 5, 10, and 15 years, while the figure shows coefficient estimates for each year. Individuals may become more patient because after experiencing a disaster they understand the importance of saving for future negative

[4]Das and Resnick (2008) recommend using quantile-quantile plots to detect fat tails.

Figure 1: Quantile-Quantile Plots for Disaster Mortality and Damages

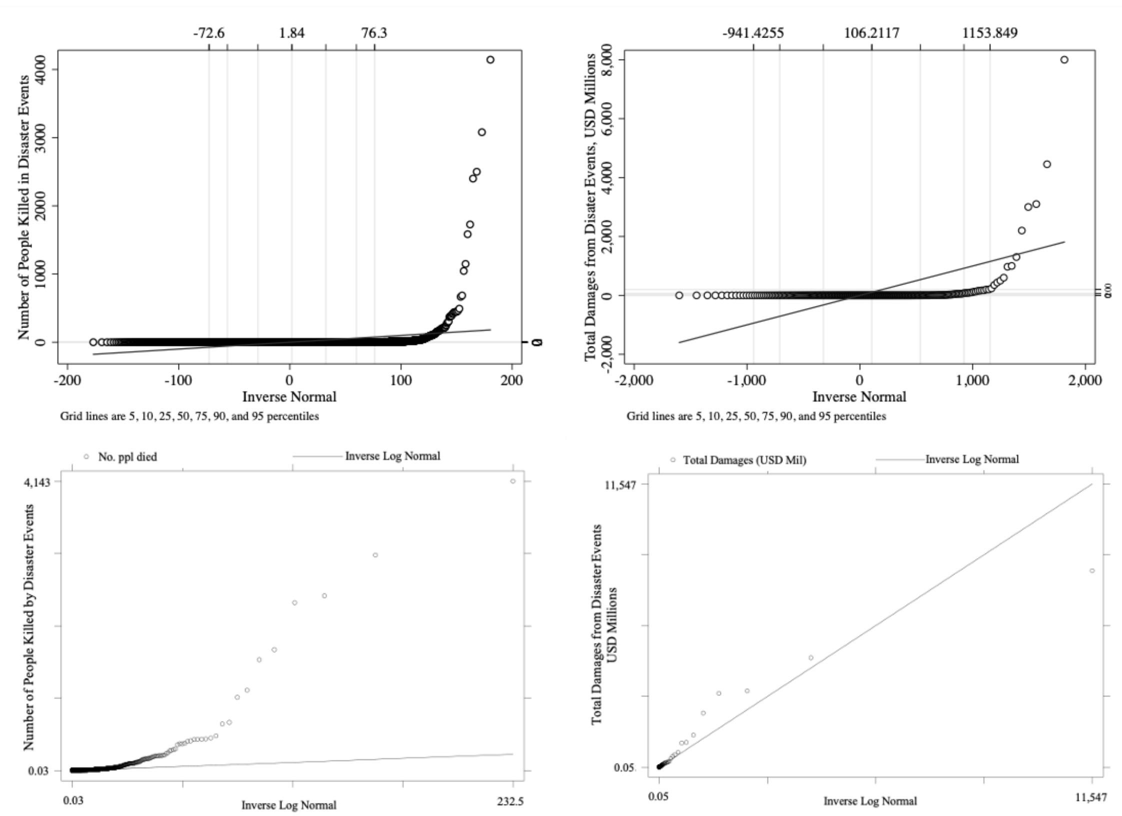

Figure Notes: The first row shows the Q-Q normal distribution plots for Deaths (left) and Damages (right) for all disaster events in Indonesia (excluding the 2004 Tsunami as this is an extreme outlier). The second row shows the same as row one, except now comparing to a log-normal distribtion (used in loss modeling by the World Bank for the Indonesian Goverment). This shows the possible underestimation of losses and mortality for extreme disaster events.

Table 5: IFLS Time Preferences

Scenario	Option 1	Option 2
	Money Today	***Money Later***
Game A		
Q1	1 million Rps Today	or 500,000 Rps. in 5 years
Q2	1 million Rps Today	or 4 million Rps. in 5 years
Q3	1 million Rps Today	or 10 million Rps. in 5 years
Q4	1 million Rps Today	or 2 million Rps. in 5 years
Game B		
Q1	1 million Rps Today	or 1 million Rps. in 1 year
Q2	1 million Rps Today	or 3 million Rps. in 1 year
Q3	1 million Rps Today	or 6 million Rps. in 1 year
Q4	1 million Rps Today	or 2 million Rps. in 1 year

shocks, or they may be receiving aid in the short term, making the choice to receive a higher amount of money later more attractive (when aid runs out).

Figure 2: Coefficient Estimates for Time on Disaster Deaths, all disasters and severe disasters

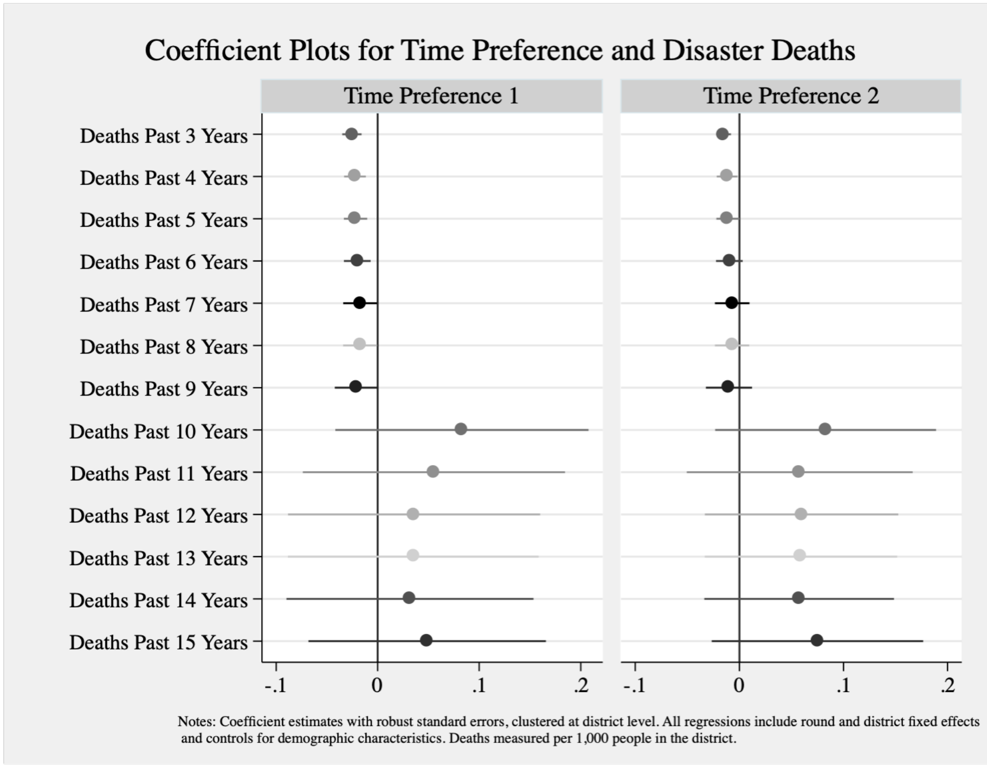

Table 6: Time Preference Category on Total District Deaths from All Disasters
adjusted for district population (per 1,000)

	Time Category			
	(1)	(2)	(3)	(4)
1-Year Mortality	-5.521**			
	(2.493)			
5-Year Mortality		-0.0218***		
		(0.006)		
10-Year Mortality			0.083	
			(0.063)	
15-Year Mortality				0.0487
				(0.059)
Avg Mortality Rate	0.002	0.084	0.171	0.175
Number of pidlink	17,825	17,825	17,825	17,825
Observations	35,650	35,650	35,650	35,650
Adjusted R-squared	0.00583	0.00493	0.00493	0.00482

Notes: Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave fixed effects, and demographic controls. Mortality rate is per 1,000 people in the district.
*** p<0.01, ** p<0.05, * p<0.1

References

Conte, Marc N and David L Kelly (submitted), "Understanding the Improbable: A Survey of Fat Tails in Environmental Economics," *Annual Review of Resource Economics* 3.

Coronese, Matteo, Francesco Lamperti, Klaus Keller, Francesca Chiaromonte, and Andrea Roventini (2019), "Evidence for sharp increase in the economic damages of extreme natural disasters," *Proceedings of the National Academy of Sciences* 116, 21450–21455.

Das, B. and S. I. Resnick (2008), "QQ Plots, Random Sets and Data from a Heavy Tailed Distribution," *Stochastic Models* 24, 103–132.