A Appendix

A.1 Summary statistics by risk category

Table A.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.

A.2 Risk Behavior

Recall that higher risk categories equate to higher risk aversion, so one would expect the relationship between risk category and risky behavior to be negative. Risk category is in fact negatively associated with all behaviors, and is most significantly associated with self-employment. When demographic controls are included, the association is no longer statistically significant for migrating for work or smoking. I also run the probit using a dummy for being in the least risk averse category (risk category equals 1). Being in this category shows higher likelihood of engaging in risky behavior, and the results are statistically significant even when controls are included (except for smoking). This makes sense as those in the least risk averse category would be the individuals most likely to engage in risky behavior.

Table A.2: Likelihood of Risky Behavior Based on Risk Category

	Migrated for Work		Self-Employed		Smoker	
	(1)	(2)	(3)	(4)	(5)	(6)
Risk Category	-0.008***	-0.004	-0.022***	-0.014***	-0.023***	-0.002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)
Demographic Controls	No	Yes	No	Yes	No	Yes
Observations	6,093	3,978	6,526	5,785	8,985	7,940
Pseudo R Squared	0.002	0.293	0.002	0.117	0.002	0.445
Least Risk Averse	0.020**	0.017**	0.058***	0.031**	0.066***	0.001
	(0.009)	(0.007)	(0.013)	(0.012)	(0.012)	(0.008)
Demographic Controls	No	Yes	No	Yes	No	Yes
Observations	4,559	3,978	6,526	5,785	8,985	7,940
Pseudo R Squared	0.003	0.295	0.002	0.116	0.003	0.445

Notes: Standard errors in parentheses, clustered at the district level. Results show average marginal effects of risk aversion on risky behavior from a probit model, controlling for interview month, sex, age, urban/rural, marital status, ethnicity, and religion, measured at wave 4. Most risky choice is a dummy for if the respondent is in risk category 1. The migrating for work probits only includes males. Smokers include people who used to smoke but have since quit. *** p<0.01, ** p<0.05, * p<0.1

A.3 Cross-sectional Results

Table 4 highlights the importance of using a fixed effects framework, showing the results of the cross sectional specification (separate results for IFLS 4 and IFLS 5), as well as the combined waves using individual and wave fixed effects. Columns 1 and 2 follow what much of the literature currently does, analyzing risk preferences at one point in time, comparing those who have experienced a disaster versus those who have not, without taking the time invariant exposure to disaster and other individual unobservables into effect. If individual unobserved heterogeneity was not an issue, the cross sectional results would not differ from the results using individual fixed effects. It is clear here that the results differ depending on which wave of data is being used, and by following individuals over time, I can observe changes in risk aversion and account for time invariant heterogeneity.[28]

In wave 4, individuals who were exposed to additional deaths are more risk averse, while in wave 5 individuals are more risk tolerant given higher levels of mortality, as seen in columns 1 and 2 of Table 4. These results may be driven by the specific timing of disasters during

Table A.3: Comparison of Cross-Sectional and Longitudinal Results

	Risk Category		
	Only IFLS4	**Only IFLS 5**	**IFLS 4 & IFLS 5**
	(1)	(2)	(3)
Deaths Past 5 Years	0.024**	-1.249**	0.085***
	(0.011)	(0.534)	(0.012)
Individual Fixed Effects	NO	NO	YES
Mean Mortality	0.172	0.012	0.092
Observations	7,947	7,947	15894
Number of respondents			7,947
Adjusted R-squared	0.021	0.011	0.020

Notes: Standard errors in parentheses, clustered at the district level. Fixed Effects regressions also include wave fixed effects. All regressions include demographic controls including sex, age, urban/rural, marital status, ethnicity, and religion. Mean number of deaths are per 1,000 people in District. *** p<0.01, ** p<0.05, * p<0.1

these two interview rounds, and do not consider differences in exposure that have existed for many years. Column 3 shows the results when both waves of IFLS data are included and accounts for individual and time fixed effects, and indicates that individual heterogeneity is likely a source of bias in the cross sectional approach. The impact of disasters on risk is now positive and significant at the 1% level. Table 5 shows that when the fixed effects approach is used, an additional 1 death per 1,000 people in the district in the last 5 years causes an increase in risk category of 0.085 (individuals become more risk averse).

A.4 Alternative Disaster Measurements

EM-DAT, the international database for disasters, reports deaths economic damages for disaster events across the globe.[29] 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.[30] 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 smaller, likely due to the measurement error associated with the disaster locations. The results of the EM-DAT regressions can be found in Table A.4. 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.[31] 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.

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 8 and 9. 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 impact on risk aversion. Because the BNBP only started tracking houses destroyed in 1999,

Table A.4: *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

Table A.5: 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

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.

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.

Table A.6: 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

A.5 Disaster Type

The type of damage and death toll often depends on whether the disaster is intensive or extensive. Extensive disasters are higher frequency, low-severity disasters such as floods, landslides, wildfire, etc. Intensive disasters are lower frequency and high-severity disasters including earthquakes, tsunamis, volcanic eruptions, etc. Floods are the most common extensive disaster in Indonesia, while earthquakes are the most common and deadly intensive disaster. Results using

Another source of differential impact of disaster on risk attitudes is the type of disaster. The type of damage and death toll often depends on whether the disaster is intensive or extensive. Extensive disasters are higher frequency, low-severity disasters such as floods, landslides, wildfire, etc. Intensive disasters are lower frequency and high-severity disasters including earthquakes, tsunamis, volcanic eruptions, etc. Floods are the most common extensive disaster in Indonesia, while earthquakes are the most common and deadly intensive disaster. When equation [2] uses floods and earthquake deaths as the D_{jt} measure, the results contrast each other. Table 10 shows that individuals become more risk averse following additional exposure to deaths from flooding, but these results disappear when looking at longer time frames. Conversely, results from the earthquake regression are consistent with the main results. There are no significant impacts at 1 and 10 years, but a statistically significant increase in risk aversion from increased earthquake deaths over the last 5 years.[32]

Table A.7: Risk Category on Total District Deaths from Floods vs. Earthquakes
adjusted for district population (per 1,000)

	Risk Category							
	Floods				**Earthquakes**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Mortality	6.141**				-26.970			
	(3.059)				(23.010)			
5-Year Mortality		3.526				0.084***		
		(2.363)				(0.012)		
10-Year Mortality			0.365				-0.095*	
			(1.217)				(0.056)	
15-Year Mortality				0.276				-0.142**
				(1.261)				(0.058)
Avg Mortality Rate	0.001	0.004	0.007	0.009	0.0002	0.079	0.162	0.162
# respondents	7,947	7,947	7,947	7,947	7,947	7,947	7,947	7,947
Observations	15,894	15,894	15,894	15,894	15,894	15,894	15,894	15,894
Adjusted R-squared	0.021	0.021	0.020	0.020	0.021	0.021	0.020	0.020

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

A.6 Results by Gender & Age

I next examine heterogeneity of the impact on risk preferences by gender and age within the sample. Table 11 shows that when equation [2] is estimated separately for women and men, the results generally hold for both. The results at the one- and 10-year time frame are insignificant. The coefficient on deaths from disasters in the district over the last five years is positive and statistically significant for both genders, but the coefficient is larger for women than men (0.092 for women vs. 0.067 for men).[33] This differs from Hanaoka, Shigeoka, and Watanabe (2018) who find significant gender differences in their results. I also find that women, especially those in households with children, have a higher positive risk response than males. Additionally, the inclusion of "gamble averse" individuals does not impact my overall results.

Table A.8: By Gender: Risk Category on Total District Deaths from Disasters
adjusted for district population (per 1,000)

	Risk Category							
	Males				**Females**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1-Year Mortality	5.475				0.995			
	(3.658)				(5.671)			
5-Year Mortality		0.079***				0.092***		
		(0.011)				(0.016)		
10-Year Mortality			-0.115				0.083	
			(0.091)				(0.097)	
15-Year Mortality				-0.129				-0.124
				(0.094)				(0.165)
Avg Mortality Rate	0.002	0.094	0.192	0.197	0.002	0.089	0.180	0.184
Number of respondents	4,559	4,559	4,559	4,079	3,868	3,868	3,868	3,868
Observations	8,158	8,158	8,158	8,158	7,736	7,736	7,736	7,736
Adjusted R-squared	0.026	0.027	0.026	0.026	0.016	0.018	0.016	0.016

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

More interesting than the slight overall differences between men and women is the difference among age groups by gender, as shown in Table 12. Frankenberg, Sumantri, and Thomas (2020) examine the impact of the 2004 Tsunami on mortality risk in the long run. They look at how community mortality rates from the tsunami influence the community mortality rate 5 and 10 years after the tsunami struck. They find that mortality risk varies among genders and different age groups and while overall there is evidence of positive mortality selection, after 10 years they find that older men have higher mortality risk due to scarring. Following the age groupings in Frankenberg, Sumantri, and Thomas (2020), I look at men and women who are under 35, between 35 and 50, and over 50 years old.

Results are presented in Table 12. While increased mortality causes increased risk aversion in the five-year time frame for both genders and most age groups, surprising patterns appear. Younger men are affected in the short term, becoming more risk averse one to five years after experiencing a disaster and the effect fades after five years, while women aged

Table A.9: Heterogeneous Effects - Coefficient Estimates By Age & Gender

	Risk Category					
	<35		**35-50**		**50+**	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
1-Year Mortality	-0.576	12.710***	0.571	-0.704	4.270	1.711
	(6.215)	(4.814)	(8.460)	(4.328)	(8.542)	(8.697)
5-Year Mortality	0.095***	0.087***	0.126***	0.034**	0.003	0.169***
	(0.014)	(0.015)	(0.035)	(0.015)	(0.026)	(0.035)
10-Year Mortality	-0.042	-0.109	0.343**	-0.139	-0.653	-0.449
	(0.118)	(0.079)	(0.168)	(0.194)	(0.745)	(0.576)
15-Year Mortality	-0.185	-0.123	0.028	-0.126	-0.842	-0.564
	(0.133)	(0.092)	(0.270)	(0.167)	(0.672)	(0.479)
Observations	4,494	4,446	2,212	2,600	1,030	1,112
Number of respondents	2,247	2,223	1,106	1,300	515	556

Notes: Table shows coefficient estimates for separate regressions of disasters deaths on risk category. Standard errors in parentheses, clustered at the district level. All regressions include individual fixed effects, wave dummy, and demographic controls. *** p<0.01, ** p<0.05, * p<0.1

35-50 have a later onset affect, becoming more risk averse five to ten years after the disaster, but not in the short term nor at the fifteen-year time frame. Additionally, the largest impact appears for men over 50 years old at the five-year time frame, with coefficient sizes double that of the overall results. This could be indicative of the income channel, where men above 50 are less able to smooth consumption over their lifetimes.

A.7 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. See the Online Appendix Section A.7 for more discussion on fat-tailed events. 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 7 which shows Quantile-Quantile Plots.[34] 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.

A.8 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

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

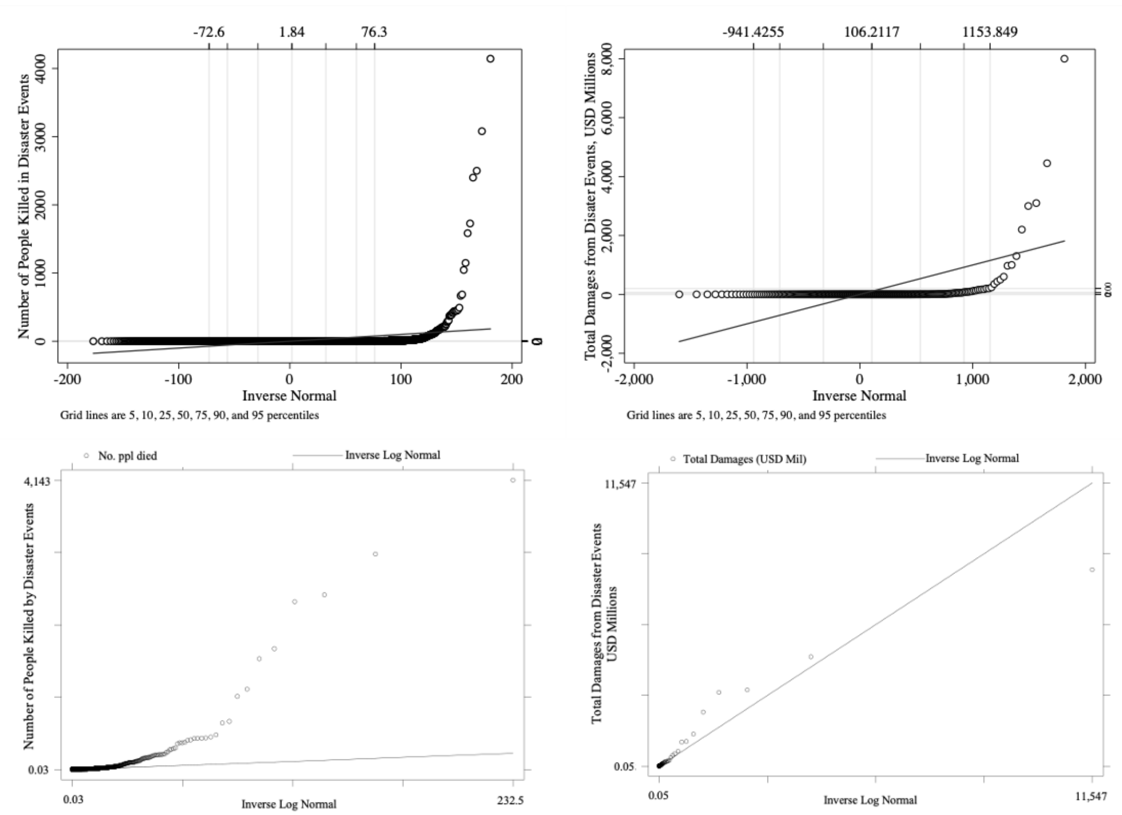

Figure Notes: The first row shows the Q-Q normal distribution plots for Deaths (left) and Damages (right) for all disaster events in Indonesia (excluding the 2004 Tsunami as this is an extreme outlier). The second row shows the same as row one, except now comparing to a log-normal distribtion (used in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

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 18.

Table A.10: IFLS Time Preferences

Scenario	Option 1 ***Money Today***	Option 2 ***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

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 22 and Figure 8. 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 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 A.2: Coefficient Estimates for Time on Disaster Deaths, all disasters and severe disasters

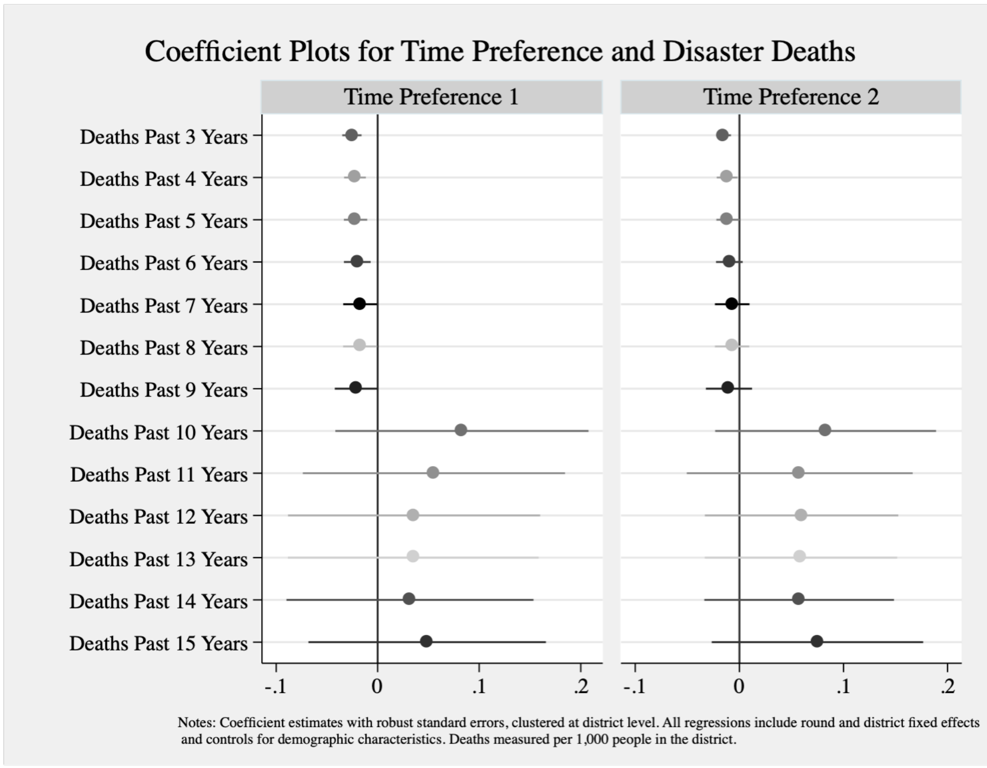

Table A.11: Time Preference Category on Total District Deaths from All Disasters
adjusted for district population (per 1,000)

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