Does climate change worsen income inequality?

Evidence from 218 countries from 1995-2022

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Background

- Climate change has become one of the most pressing concerns in today's world, manifesting through rising sea levels, changes in precipitation patterns, more severe and frequent extreme weather events, and other environmental disruptions.
- Income inequality can restrict social mobility, curtail economic growth, and weaken faith in government and institutions. While income inequality between countries has improved in recent decades, income inequality within countries has generally worsened.
- The association between climate change and income inequality is an emerging topic of research. Existing literature contains mixed results, with the most prevalent conclusion being that climate change exacerbates income inequality to some extent.
- Budina, Chen and Nowzohour (2023) find that pre-existing macroeconomic and socioeconomic vulnerabilities and the type, frequency, and severity of climate disasters can intensify the impact of disasters on income inequality.
- Disasters disproportionately impact low-income populations and countries, as poorer societies often lack means to rebuild after disasters and low-income groups are often limited to living in undesirable locations prone to climate shocks. (Ogbeide-Osaretin et al. 2022, Islam and Winkel 2017). However, climate change may impact low-income populations to a lesser extent than high-income ones. Keerthiratne and Tol (2018) find that disasters decrease income inequality in Sri Lanka and postulate that this surprising result may be because, "at subsistence level, people possess little that can be lost to a natural disaster," but wealthier groups have more to lose.

Data

Dependent Variable: Gini Index
Critical Independent Variable: Frequency of climate-related disasters
Control Variables: GDP per capita, total population, readiness to handle climate change impacts
This study uses panel data for 218 countries for the years 1995 through 2022. Gini and Readiness have a two-year lag to account for the time it takes for their effects to show in the Gini index.

Table 1: Summary Statistics

Variable	Abbrev.	N	Mean	Std Dev	Min.	Max.	Source
Gini index	Gini	1807	37.541	8.565	23	65.8	World Bank
Frequency of climate-related disasters	Cdisaster	3023	2.934	3.825	1	43	IMF, EM-DAT
GDP per capita	GDPpc	5623	14629.6	21763.94	210.542	228667.9	World Bank
Total population	Pop	6076	31470225	126261238	9585	1417173173	World Bank
Readiness to handle climate change impacts	Readiness	5184	0.406	0.135	0.115	0.855	ND-GAIN Country Index

Models

(1) Pooled

$$Gini_{it} = \beta_0 + \beta_1 Cdisaster_{it-2} + \beta_2 Ln(GDPpc)_{it} + \beta_3 Ln(Pop)_{it} + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}{*}Readiness_{it-2} + \epsilon i_t$$

(2) Country-fixed effects

$$Gini_{it} = \beta_0 + \beta_1 Cdisaster_{it-2} + \beta_2 Ln(GDPpc)_{it} + \beta_3 Ln(Pop)_{it} + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}{*}Readiness_{it-2} + \alpha_i + \epsilon i_t$$

(3) Time-fixed effects

$$Gini_{it} = \beta_0 + \beta_1 Cdisaster_{it-2} + \beta_2 Ln(GDPpc)_{it} + \beta_3 Ln(Pop)_{it} + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}{*}Readiness_{it-2} + \gamma_t + \epsilon i_t$$

(4) Country and time-fixed effects

$$Gini_{it} = \beta_0 + \beta_1 Cdisaster_{it-2} + \beta_2 Ln(GDPpc)_{it} + \beta_3 Ln(Pop)_{it} + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}{*}Readiness_{it-2} + \alpha_i + \gamma_t + \epsilon i_t$$

(5) Between Estimates

$$Gini_i = \beta_0 + \beta_1 Cdisaster_i + \beta_2 Ln(GDPpc)_i + \beta_3 Ln(Pop)_i + \beta_4 Readiness_i + \beta_5 Cdisaster_i * Readiness_i + \epsilon_{it}$$

(Average Gini, GDPpc, and Pop from 2010-2022; average Cdisaster and Readiness from 1995-2009)

Results

Table 2: Comparison of Models' Results

Variable	(1)	(2)	(3)	(4)	(5)
Cdisaster	-0.630**	0.056	-0.509**	0.157	0.314
	(0.261)	(0.133)	(0.247)	(0.139)	(0.461)
GDPpc	3.055***	-4.951***	3.158***	-1.984	0.001*
	(0.810)	(1.208)	(0.797)	(1.498)	(0.00004)
Pop	-0.049	-6.146***	-0.109	0.305	-0.389
	(0.542)	(2.270)	(0.543)	(2.902)	(0.321)
Readiness	-66.652***	4.397	-66.265***	12.728***	-39.859***
	(8.695)	(3.610)	(8.333)	(3.877)	(6.614)
Cdisaster*Readiness	1.746***	0.124	1.546***	-0.118	0.452
	(0.409)	(0.220)	(0.379)	(0.194)	(0.705)
Constant	41.233***				57.174***
	(9.954)				(5.392)
R^2	0.364	0.218	0.361	0.046	0.227
Adjusted R^2	0.362	0.106	0.343	-0.120	0.200
AIC	7720.57	5282.939	7665.066	5180.227	1017.971
BIC	7755.89	5313.214	7695.341	5210.502	1039.184
Observations	1,148	1,148	1,148	1,148	153

*p<0.1, **p<0.05, ***p<0.01

Marginal Effect of Cdisaster on Gini

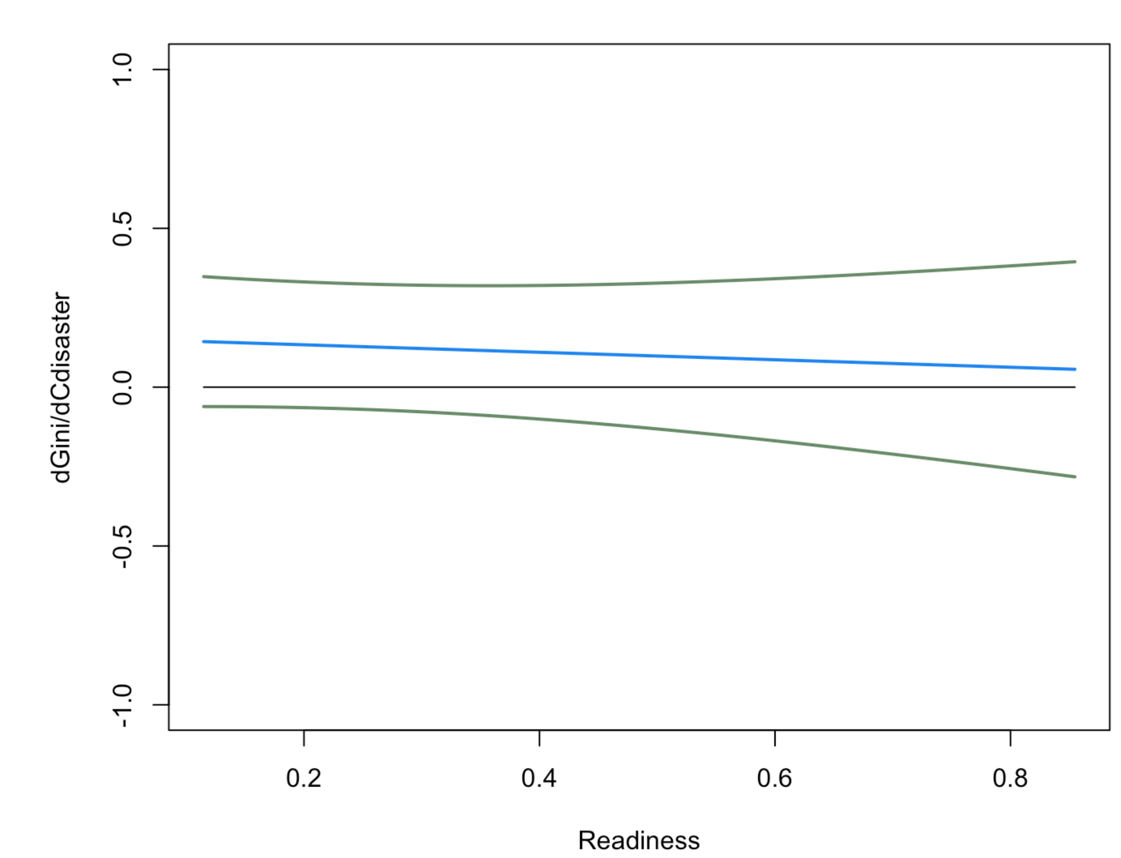
Central Hypothesis: the occurrence of climate-related disasters in a country increases the country's income inequality and that this effect takes a couple of years to show in the Gini index.
H_0: $\partial Gini/\partial Cdisaster = \beta_1 + \beta_5 Readiness > 0$
(holding all else included constant, a one-unit increase in Cdisaster results in a positive change in Gini)

My models provide mixed results pertaining my central hypothesis. $\partial Gini/\partial Cdisaster$ is positive for the entire range of Readiness in Models 2, 4, and 5, which aligns with my theory. However, in Models 1 and 3, the marginal effect is negative for a range of low Readiness levels.

Existing research and theory indicate that a higher level of readiness may mitigate the impact of climate change on income inequality. This is only the case for Model 4, while the rest of my models show that $\partial Gini/\partial Cdisaster$ increases as Readiness increases.

Supplemental Hypothesis: H_0: $\beta_1 = 0$ (no effect of Cdisaster on Gini) and $\beta_5 = 0$ (no interaction term between Cdisaster and Readiness)
F-tests reject the null hypothesis that $\beta_1 = 0$ and $\beta_5 = 0$.

Figure 1: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals Using Model 4

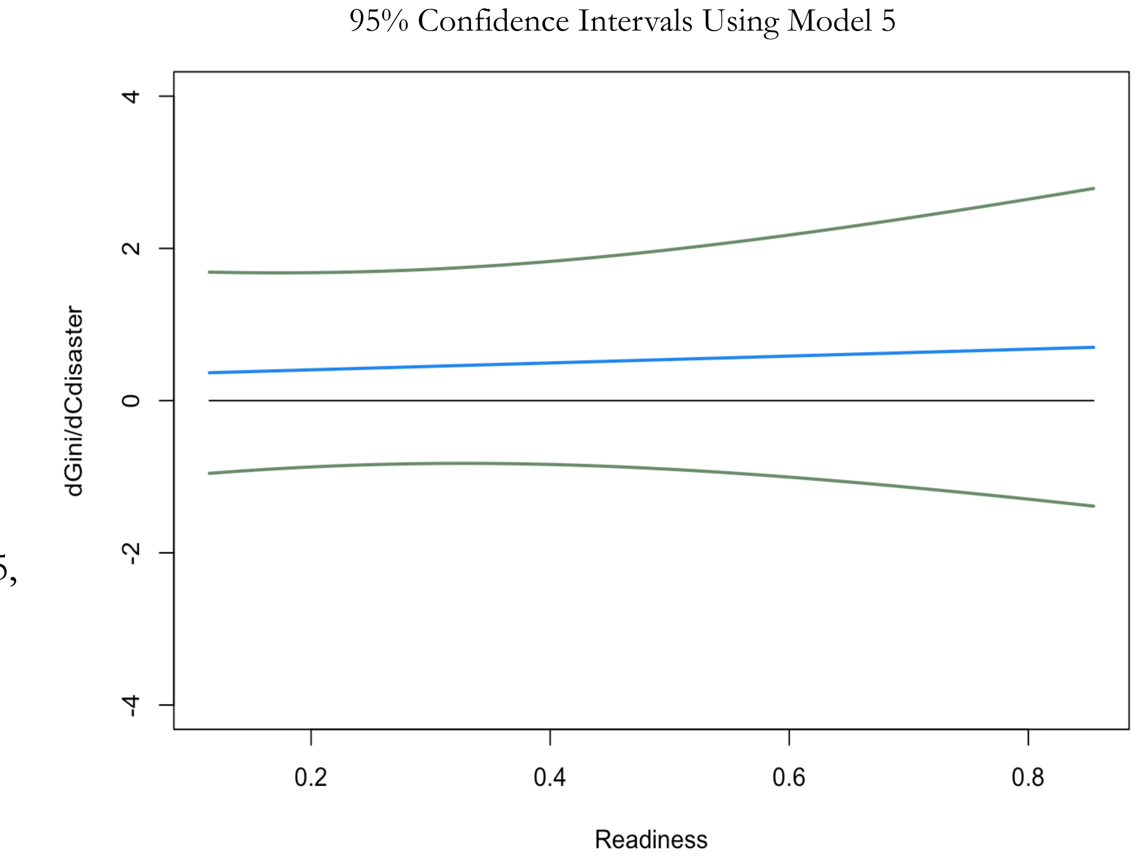


Concerns and Robustness Check of Between Estimates Model

My dataset is unbalanced, containing missing values for Gini and Cdisaster.
Readiness may be endogenous. Wealthier countries may be more ready to handle class impacts, and GDPpc is a control variable in my models.

As a robustness check, I included Model 5, a between estimates model. For each country, I averaged Cdisaster and Readiness from 2009 and Gini, GDPpc, and Pop from 2010-2022. I estimated the averaged Gini from the latter time-period as a function of the averaged independent variables, with Cdisaster and Readiness being from the first time-period and GDP pc and Pop being from the latter time-period.
This model yielded a positive $\partial Gini/\partial Cdisaster$, though, as Readiness increases, $\partial Gini/\partial Cdisaster$ increases. $\partial Gini/\partial Cdisaster$ is surprisingly higher for higher Readiness levels in most of my models.

Figure 2: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals Using Model 5



Comparison of Models

Comparing R^2 and adjusted R^2 values suggests that Model 1, the pooled model, has the highest explanatory power. Interestingly, the addition of fixed effects (Model 2, 3, 4, and 6) results in lower R^2 and adjusted R^2 values.

Comparing AIC and BIC values suggests that Model 4, the model with country and time fixed effects, and Model 5, the between estimates model included as a robustness check, are the best fits.

F-tests indicate that the models with fixed effects are better fits than the pooled model. Furthermore, F-tests propose that Model 4 with both country and time-fixed effects is a better fit than the models with only country or time-fixed effects. Thus, F-tests seem to support that Model 4 is the best overall fit.

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