The Complex Relation between Climate Change and Income Inequality: An Analysis of 218 Countries from 1995-2022

Climate change and income inequality have become increasingly prominent issues in recent years, though the complex relationship between the two has gone less studied. Climate change, which the United Nations defines as “long-term shifts in temperatures and weather patterns,” poses a fundamental threat to societies and ecosystems around the globe. Human activities, like deforestation and fossil fuel burning, have been the primary cause of recent climate change. Climate change has become one of the most pressing concerns in today’s world, manifesting through rising sea levels, melting glaciers, precipitation pattern changes, more severe and frequent extreme weather events, and more environmental disruptions. High levels of income inequality, which refers to the uneven distribution of income among a population, have detrimental social and economic consequences for a society. Income inequality can restrict social mobility, curtail economic growth, and weaken faith in government and institutions. While inequality between countries has improved in recent decades, income inequality within countries has generally worsened.[1]

The relationship between climate change and income inequality is an emerging area of research. The central question research seeks to answer is: does climate change income inequality? Climate change may impact income inequality through several channels. Climate-induced degradation of ecosystems and extreme weather events can disrupt economic activity, damaging infrastructure, supply chains, forests, agriculture, and other avenues of economic production. Climate change can hurt the health of populations, limiting access to clean water sources, sanitation, and healthcare and increasing air pollution, heat waves, and some diseases. Additionally, climate change does not impact every country equally. Low-income countries, that likely have fewer resources and limited adaptive capacities, tend to feel the impacts of climate change to a greater degree than countries with access to resources and infrastructure for climate protection. Poor countries also tend to be in locations very susceptible to climate change, such as hot or flood-prone regions. Thus, even though wealthier countries are responsible for the majority of greenhouse gas emissions, poorer countries feel the brunt of the impacts.

This paper examines the relationship between climate change and income inequality, the central hypothesis being that climate change exacerbates income inequality within countries. Additionally, I examine whether countries less equipped to handle climate change exhibit greater levels of income inequality.

I. *Literature Review*

Despite the relatively low quantity of research on the intersection between climate change and income inequality, income inequality itself is well-studied. There are a multitude of macroeconomic, socioeconomic, and demographic factors that influence a country’s income inequality. Studies typically point to education, political stability, and government policy as key determinants. Education promotes social mobility, opening up employment opportunities and influencing pay. Political stability enables governments to effectively implement policies; whereas, turmoil and corruption within governments breed mistrust among citizens and restrict long-term development. The impact of government policies on inequality depends on the policy. For instance, public spending on healthcare and redistributive cash transfers can decrease income inequality. These are some key determinants of income inequality, but certainly not all. The Gini index is a typical measure of income inequality for countries.

Existing research on the link between climate change and income inequality uses a variety of measurements for climate change. Common indicators in existing studies include temperature, precipitation, sea levels, and extreme weather events. The relationship between temperature and inequality is relatively well-studied, with the literature agreeing that a non-linear, U-shaped relationship exists between temperature and inequality. Hence, inequality is the lowest at moderate temperatures and highest at low and high temperatures. For countries in colder climates, warming shifts them to

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[1]In particular, advanced economies have witnessed worsening income inequality. A few developing countries have experienced reductions in income inequality.

temperatures more conducive for lower income inequality. For warm countries, temperature rises only further increase income inequality. Using the Gini index as an estimate of within-country income inequality, findings from Dang, Nguyen and Trinh (2023), Dasgupta, Emmerling and Shayegh (2023), and Ogbeide-Osaretin *et al.* (2022) support the parabolic relationship between temperature and income inequality. Dang, Nguyen and Trinh (2023) examine global data, while Dasgupta, Emmerling and Shayegh (2023) focus on South Africa and Ogbeide-Osaretin *et al.* (2022) on Nigeria.

A novel indicator called the Notre Dame-Global Adaption Country Index (ND-GAIN) evaluates a country's vulnerability to climate change and readiness to adapt. Using this index, Cevik and Jalles (2022) analyze how climate change impacts income inequality in 158 countries from 1995-2019. In terms of vulnerability, their analysis reveals that an increase in vulnerability results in higher income inequality in general. Splitting their sample into two income groups reveals that vulnerability has no statistically significant impact on income inequality for advanced economies, while it has a much larger and highly significant impact in developing countries. In terms of the readiness (also referred to as "resilience") component, Cevik and Jalles (2022) determine that "an increase in climate resilience is associated with lower income inequality" (though they note that this effect is not statistically significant when using the net Gini index instead of market Gini index as a measure of income inequality).

Another indicator of climate change is extreme weather events, as climate change has been shown to increase the frequency and severity of weather disasters (Skidmore and Toya 2002). Examining climate-related disasters has yielded mixed results in the literature. Budina, Chen and Nowzohour (2023) find that the impact of climate disasters on income inequality "varies based on their severity, whether they are associated with growth slowdowns, their frequency of occurrence within the same year, the type of disaster, and the country's income status." The study observes that disasters consistently worsen income inequality in advanced economies but that the effect on emerging and developing economies is more contingent upon the other conditions (i.e., severity, type, and frequency of disaster and whether a concurrent growth slowdown accompanied the disaster). Climate disasters disproportionately impact low-income populations, as poorer communities often lack the infrastructure and resources to rebuild after disasters (Ogbeide-Osaretin *et al*. 2022). Additionally, low-income populations are often limited to living in undesirable locations prone to climate shocks, such as areas that are low-elevation and prone to flooding or arid and prone to droughts (Islam and Winkel 2017). Keerthiratne and Tol (2018) write, "Natural disasters disproportionally affect the poor. It is therefore often assumed that natural disasters increase income inequality." Instead, they find that disasters decrease income inequality in the case of Sri Lanka. They postulate that, "though the poor are more vulnerable to disasters, when the poor live a subsistence lifestyle and if they do not possess or own much material assets, their losses will be less compared to the rich." This aligns with Budina, Chen, and Nowzohour (2023), as both studies emphasize that affluent populations are most likely to experience increases in income inequality due to climate disasters. Analyzing panel data for 86 countries from 1965 to 2004, Yamamura (2015) finds that natural disasters increase income inequality in the short-run, but that this effect is not present long-term. In conclusion, theory indicates that climate change exacerbates income inequality; however, the specific effect of climate-related weather disasters has mixed results. Under certain circumstances and for advanced economies, studies find a significant, positive relationship between climate disasters and within-country income inequality.

II. Model Development

My models estimate the Gini index, with the functional forms being lin-logs. Table 1 presents my models and hypotheses. The frequency of climate-related disasters in a country (denoted "Cdisaster") is my critical independent variable and empirical proxy for climate change. I control for GDP per capita, population, and readiness (the capacity to adapt to climate change). Existing studies typically include GDP per capita and population to isolate the impact of climate change. As is a common practice in econometrics, the GDP per capita and population variables are logged. Taking logarithms normalizes variables and is a common practice for variables with outliers or variables generated through multiplicative processes. I include an interaction term between Cdisaster and Readiness, as studies postulate that the effect of climate disasters on income inequality depends on a country's readiness for adaptation. I postulate a lagged effect of my critical independent variable, Cdisaster, on my dependent variable, Gini. Existing literature hypothesizes that the impact of climate disasters takes time to manifest in the Gini index and that there may be delays in how quickly governments and economies respond to climate change. Studies typically include 1 to 5-year lags to examine the long-run impact and cumulative effects of climate change. Readiness is lagged as well, as I theorize that the impactful readiness level is that which was present when the disasters occurred. Models 1-4 are panel models, with Model 1 being pooled, 2 including country-fixed effects, 3 including time-fixed effects, and 4 including both country and time-fixed effects.

My central hypothesis is that 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. Algebraically, this is represented as $\partial Gini_{it}/\partial Cdisaster_{it-2} = \beta_1 + \beta_5 Readiness_{it-2} > 0$. As this equation shows, the marginal effect of Cdisaster on Gini depends on a country's readiness level. I include the supplemental hypothesis $\beta_1 = 0$ to check if Cdisaster has no effect on Gini and $\beta_5 = 0$ to check if there is no interaction between Cdisaster and Readiness. I test these hypotheses for each model.

III. Data and Statistical Assumptions

My paper uses the Gini index to measure income inequality. The Gini index indicates the extent to which income distribution deviates from a perfectly equal distribution, with 0 representing perfect equality and 100 perfect inequality.

The Emergency Events Database (EM-DAT) contains widely cited disaster data. The EM-DAT records disasters that caused at least 10 fatalities, affected at least 100 people, caused a declaration of a state of emergency, and/or caused a call for international assistance. From the EM-DAT, the International Monetary Fund (IMF)'s Climate Change Dashboard compiles a climate indicator titled "climate-related disasters frequency," which encompasses only climate-related disasters. This covers wildfires, storms, landslides, floods, extreme temperatures, drought, fog, wave actions, and glacial lake outbursts.

The ND-GAIN Country Index aggregates 45 indicators of vulnerability to and readiness concerning climate change. Vulnerability refers to the predisposition of a country to be negatively impacted by climate hazards. Readiness refers to a country's ability to effectively use investments for adaptation. Economic, governance, and social readiness are the three types that combine to produce a country's overall readiness. Economic readiness is defined as the "investment climate that facilitates mobilizing capital from the private sector" (*Country Index Technical Report*, 2023). Government readiness is a combination of political stability and non-violence, control of corruption, rule of law, and regulatory quality. Social readiness is a combination of "social conditions that help society to make efficient and equitable use of investment and yield more benefit from the investment," such as education and information communication technology (ICT) infrastructure (*Country Index Technical Report*, 2023). Many of the indicators that are combined to produce the readiness score of the ND-GAIN index come from World Bank data. The ND-GAIN Country Index can be split into its vulnerability and readiness components, and my models will control for the readiness component. Doing so controls for determinants of income inequality, like education and political stability, discussed in my literature review.

My dataset merges panel data from multiple sources and covers 218 countries from 1995 to 2022. The unit of analysis is country-year. The data for GDP per capita, population, and Gini index come from the World Bank. The data for the readiness score is from the Notre Dame Global Adaptation Initiative's ND-GAIN Country Index. The data for climate-related disaster frequency comes from the International Monetary Fund. Table 2 represents my variables and data sources. The main limitation of my dataset is that it is unbalanced. There are missing values for the Gini and Cdisaster variables. Another limitation is that the data comes from different sources, which cover slightly different sets of countries. However, I largely resolved this issue when I merged the data in Excel.

Table 3 provides summary statistics for my dataset and units of measurement for the variables. The mean Gini coefficient is 37.541. The maximum Gini measured is 65.8, which corresponds to Malawi in 1997, and the minimum is 23, which corresponds to Denmark in 1995. The mean number of climate-related disasters is 2.934. The maximum recorded number of climate-related disasters is 43, which occurred in the United States in 2021. The average Readiness is 0.406, the minimum is 0.115, corresponding to the Central African Republic in 2014, and the maximum is 0.855, corresponding to Monaco in 2017. The skewness is positive for every variable, meaning the data for each variable is skewed to the right. Population has the highest skewness at 8.975, followed by Cdisaster at 4.336. In terms of kurtosis, the two variables that are indexes, Readiness and Gini, are the closest to mesokurtic with kurtoses of around three. The other variables are leptokurtic, as their kurtoses are higher than three, indicating that their distributions have heavy tails and that the data may be prone to outliers.

IV. General Empirical Results

Table 4 provides my full regression results for each model. This section will highlight a few key takeaways from the table, focusing specifically on comparing the fits of my models. The coefficient of determination, one measure of the goodness of fit of a model, represents the proportion of variance in the dependent variable that is explained by the independent variables. Model 1, the pooled model, has the highest R^2, which suggests it has the greatest explanatory power. Surprisingly, the addition of fixed effects results in lower R^2 values. AIC and BIC are other measures of the goodness of fit of models that take into account the number of variables included. The AIC and BIC for Models 2 and 4 are in the 5000s, while the AIC and BIC for Models 1 and 3 are in the 7000s. Model 4 with country and time-fixed effects has the lowest AIC and BIC, which suggests it is the best fit. Looking at adjusted R^2, which adjusts for the number of variables included, indicates that Model 1 is the best fit. The addition of fixed effects also yields lower adjusted R^2 values. 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. Interestingly, Model 4 has the lowest R^2 and adjusted R^2, but AIC, BIC, and F-tests point to Model 4 as the best fit.

V. Interpretation of the Empirical Results

Existing literature and research generally conclude that climate change exacerbates income inequality; however, the specific effect of climate-related disasters on income inequality yields mixed results, which aligns with my findings. To recap from my literature review, studies find a significant, positive effect of disasters on income inequality under certain conditions. The type, frequency, and severity of a disaster and whether a simultaneous economic growth slowdown accompanied the disaster may strengthen climate change impacts on inequality (Budina, Chen, and Nowzohour 2023). Country income may determine whether climate change affects the country's Gini index in a positive or negative direction (Keerthiratine and Tol 2018). "The resilience of institutions and physical infrastructure" and "the capacity for mitigation and adaption to climate change" may also play a role (Cevik and Jalles 2022). Climate change's effect on income inequality may differ in the short versus long run as well (Yamamura 2015). My models leave me with mixed results, some of which support and some of which are incongruent with the hypothesis from the literature that climate change increases income inequality. Pertaining to my central hypothesis, Figures 1-4 below depict the marginal effect of Cdisaster on Gini for the entire range of Readiness and 95% confidence intervals and for each model. I expected ∂Gini/∂Cdisaster to be positive, meaning that climate disasters exacerbate income inequality. This is the case for Models 2 and 4. For Models 1 and 3, the marginal effect is negative for a range of low Readiness levels. As Figures 1 and 3 show, the range of Readiness levels for which the marginal effect is positive is wider than the range for which the effect is negative. Figures 2 and 4 show ∂Gini/∂Cdisaster as only positive for Models 2 and 4 respectively. Models 2 and 4 also have the lowest AIC and BIC.

Additionally, I expected that a higher level of readiness may mitigate the impact of climate change; and, thus, that ∂Gini/∂Cdisaster would decrease as Readiness increases. This is the case for Model 4, but the rest of my models show ∂Gini/∂Cdisaster increasing as Readiness increases. As previously discussed, goodness of fit measures AIC, BIC, and F-tests point to Model 4 as the best fit comparatively. My models yield mixed results concerning the effect of Readiness, as does existing research. Cevik and Jalles (2022) found that a higher degree of readiness to handle climate change impacts may be associated with lower income inequality, but that the significance of this effect is subject to uncertainty. One concern is that Readiness may be an endogenous variable. Wealthy countries may be more ready to handle climate change impacts, and GDP per capita is a control variable in my models. In the literature, Keerthine and Tol (2018) find that disasters surprisingly decrease income inequality in their sample of Sri Lanka; they hypothesize that low-income populations possess less to lose when disasters hit than wealthy populations, and, thus, climate change may impact poor populations to a lesser degree.

In terms of my supplemental hypotheses, F-tests reject the null that $\beta_1 = 0$ (no effect of Cdisaster on Gini) and $\beta_5 = 0$ (no interaction term between Cdisaster and Readiness) for all models. Economic theory predicts that the frequency of climate-related will impact the Gini index. And, this effect may depend on a country's "readiness" to adapt to climate change (Cevik and Jalles 2022). Thus, my conclusion here aligns with the existing results.

To address limitations of my dataset and concerns with my results, I estimated Model 5, a between-estimates model, as a robustness check. My dataset is missing values for Gini and Cdisaster variables and my models yielded some opposing results on the relationship between climate disasters and income inequality. I split my sample into two time periods: 1995-2009 and 2010-2022. The Gini index, GDP per capita, and population variables are averaged for each country for the latter time period, 2010-2022. The frequency of climate disasters and readiness variables are averaged for each country from the first time period, 1995-2009. As previously discussed, the effects of climate change likely take time to manifest, so the Gini and Readiness indicators contain a lag in all of my other models (Models 1-4). Thus, it follows that, for this between estimates model, Gini and Readiness correspond to the first time period. Model 5's AIC is 1017.971 and BIC is 1039.184, which are the lowest of all models. Model 5's R^2 is 0.227 and adjusted R^2 is 0.200, which places Model 5 at the median in terms of these measures. ∂Gini/∂Cdisaster for Model 5 is positive for all levels of Readiness, confirming my central hypothesis that the marginal effect of Cdisaster on Gini is positive. As Figure 5 shows, ∂Gini/∂Cdisaster increases only slightly as Readiness increases.

VI. Summary and Conclusions

Analyzing data on 218 countries from 1995-2022, my paper examines the effect of climate change on within-country income inequality. My work seeks to contribute to existing literature on the question: does climate change increase income inequality? I use annual, country-level data on the frequency of climate-related disasters to measure climate change and on the Gini index to measure income inequality. My central hypothesis is that climate-related disasters increase income inequality within-country income inequality and that this effect takes time to manifest in the Gini index. I postulate four core panel models, a pooled model, a country-fixed effects model, a time-fixed effects model, and a country-and-fixed effects model. I estimate my central hypothesis algebraically from my models as $\partial \text{Gini}_{it}/\partial \text{Cdisaster}_{it-2} = \beta_1+\beta_5 \text{Readiness}_{it-2} > 0$. My models support my central hypothesis, albeit with varying levels of support across models, as Figures 1-4 reveal. Additionally, I anticipated that a higher level of readiness to adapt to climate change would mitigate the impacts of climate disasters, resulting in a lower ∂Gini/∂Cdisaster. Models 1-3 find the opposite, as corresponding Figures 1-3 show. However, Model 4 with country and time-fixed effects support this theory, as depicted in corresponding Figure 4.

Concerns with my research include that I obtained mixed results across my models and that my dataset is unbalanced, lacking complete data for the Gini index and frequency of climate disasters. To address the limitations of my dataset and concerns regarding model robustness, I employed Model 5, a between-estimates model. Model 5 supports my central hypothesis, as corresponding Figure 5 shows. Overall, my empirical analyses find some support that climate disasters exacerbate income inequality. However, the relationship between climate change and income inequality is complex and warrants further research to unpack the many dynamics at play.

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Tables and Figures

Table 1: Functional Forms of Models and Hypotheses

Model (1) – Pooled
$Gini_{it} = \beta_0 + \beta_1 Cdisaster_{it-2} + \beta_2\ Ln(GDPpc_{it}) + \beta_3 Ln(Pop_{it}) + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}*Readiness_{it-2} + \epsilon_{it}$

Model (2) – Country-Fixed Effects
$Gini_{it} = \beta_1 Cdisaster_{it-2} + \beta_2\ Ln(GDPpc_{it}) + \beta_3 Ln(Pop_{it}) + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}*Readiness_{it-2} + \alpha_i + \epsilon_{it}$

Model (3) – Time-Fixed Effects
$Gini_{it} = \beta_1 Cdisaster_{it-2} + \beta_2\ Ln(GDPpc_{it}) + \beta_3 Ln(Pop_{it}) + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}*Readiness_{it-2} + \gamma_t + \epsilon_{it}$

Model (4) – Country and Time-Fixed Effects
$Gini_{it} = \beta_1 Cdisaster_{it-2} + \beta_2\ Ln(GDPpc_{it}) + \beta_3 Ln(Pop_{it}) + \beta_4 Readiness_{it-2} + \beta_5 Cdisaster_{it-2}*Readiness_{it-2} + \alpha_i + \gamma_t + \epsilon_{it}$

Model (5) – Between Estimates
$Gini_t = \beta_1 Cdisaster_i + \beta_2\ Ln(GDPpc_i) + \beta_3 Ln(Pop_i) + \beta_4 Readiness_i + \beta_5 Cdisaster_i*Readiness_i + \epsilon_i$

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

Central Hypothesis	H_0: $\partial Gini_{it}/\partial Cdisaster_{it-2} = \beta_1+\beta_5 Readiness_{it-2} > 0$ (holding all else included constant, a one-unit increase in $Cdisaster_{t-2}$ results in an increase in $Gini_{it}$)
Supplemental Hypothesis	H_0: $\beta_1 = 0$ (no effect of Cdisaster on Gini) and $\beta_5 = 0$ (no interaction term between Cdisaster and Readiness)

Table 2: Variable Index

Variable	Meaning	Source
Cdisaster	Frequency of climate-related disasters	International Monetary Fund (IMF)'s Climate Change Dashboard, Emergency Events Database (EM-DAT)
GDPpc	GDP per capita (constant 2015 USD)	World Bank's World Development Indicators
Gini	Gini index	World Bank's World Development Indicators
Pop	Total population	World Bank's World Development Indicators
Readiness	Readiness to handle climate change impacts	Notre Dame Global Adaptation Initiative's ND-GAIN Country Index

Table 3: Summary Statistics

	Gini	Cdisaster	GDPpc	Pop	Readiness
Average	37.541	2.934	14,629.6	31,470,225	0.406
Standard Deviation	8.565	3.825	21,763.94	126,261,238	0.135
Minimum	23	1	210.542	9,585	0.115
First Quartile	31.1	1	1,761.506	663,570.5	0.305
Median	35.6	2	5,141.731	5,473,301	0.374
Third Quartile	42.65	3	18,659.59	19,816,137	0.478
Maximum	65.8	43	228,667.9	1,417,173,173	0.855
Skewness	0.709	4.336	2.921	8.975	0.838
Kurtosis	2.796	27.049	15.368	89.334	3.168
Number of Obs	1,807	3,023	5,623	6,076	5,184
Units of Measurement	No units, index scale	Number of disasters	Constant 2015 USD	Number of persons	No units, index scale

Table 4: Comparison of Models

	Depdendent Variable: Gini Index, 1995-2022				
	(1)	(2)	(3)	(4)	(5)
Model Type	Pooled	Country-Fixed Effects	Time-Fixed Effects	Country and Time-Fixed Effects	Between Estimates
Cdisaster	-0.630** (0.261)	0.056 (0.133)	-0.509** (0.247)	0.157 (0.139)	0.314 (0.461)
GDPpc	3.055*** (0.810)	-4.951*** (1.208)	3.158*** (0.797)	-1.984 (1.498)	0.001* (0.00004)
Pop	-0.049 (0.542)	-6.146*** (2.270)	-0.109 (0.543)	0.305 (2.902)	-0.389 (0.321)
Readiness	-66.652*** (8.695)	4.397 (3.610)	-66.265*** (8.333)	12.728*** (3.877)	-39.859*** (6.614)
Cdisaster*Readiness	1.746*** (0.409)	0.124 (0.220)	1.546*** (0.379)	-0.118 (0.194)	0.452 (0.705)
Constant	41.233*** (9.954)				57.174*** (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	1039.183
Observations	1,148	1,148	1,148	1,148	153

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

Figure 1: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals (Model 1)

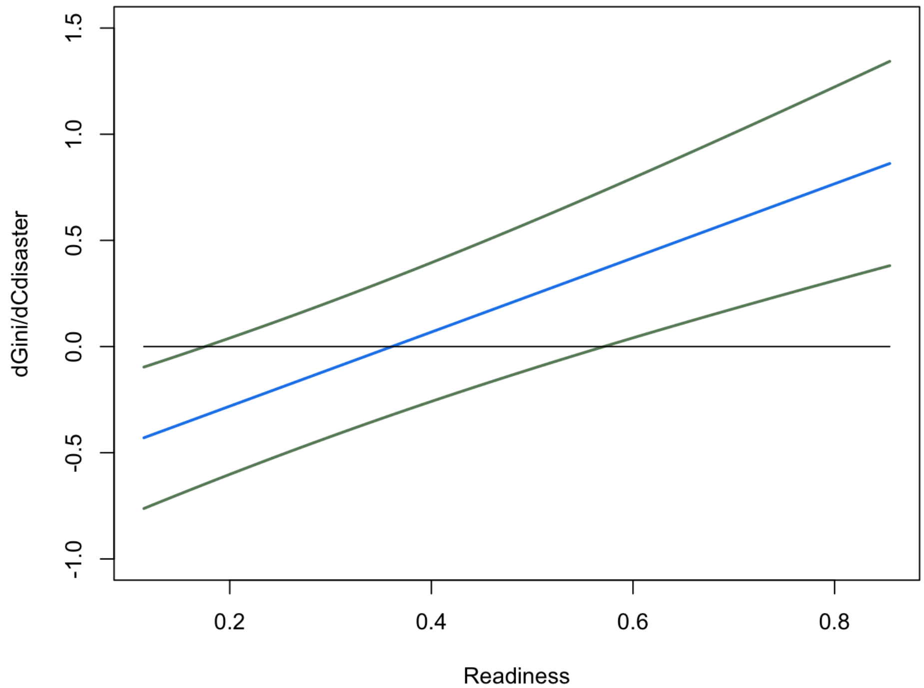

Figure 2: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals (Model 2)

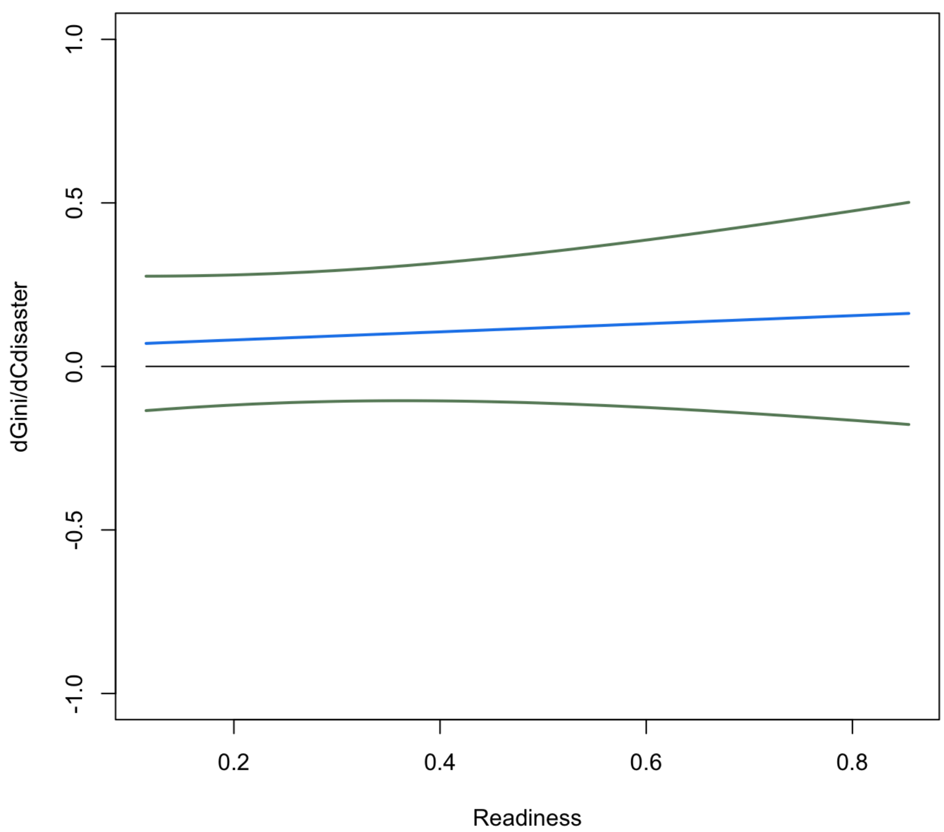

Figure 3: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals (Model 3)

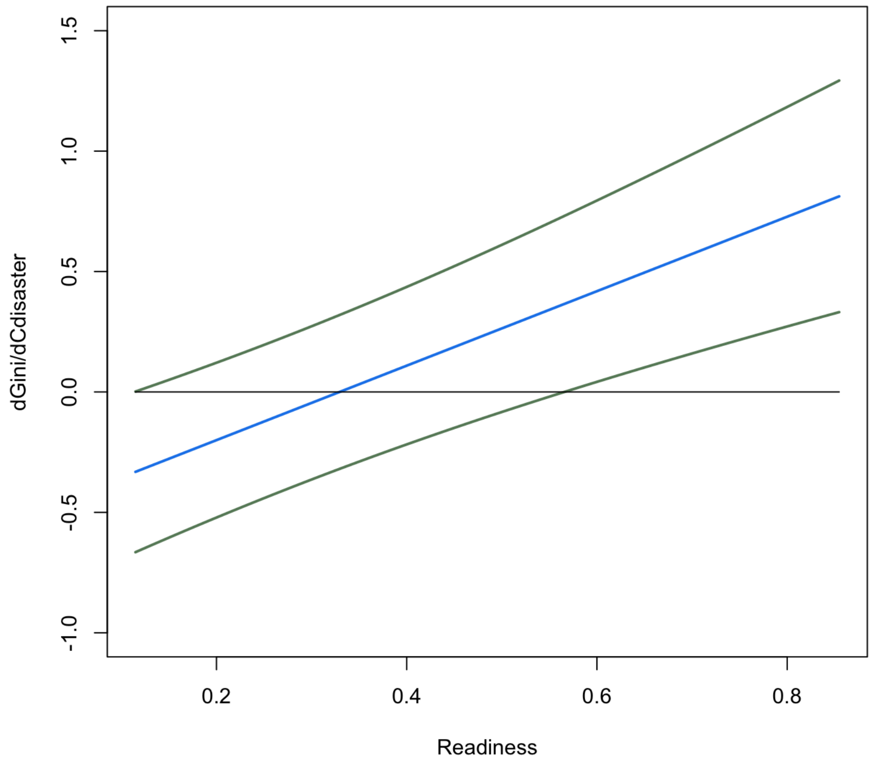

Figure 4: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals (Model 4)

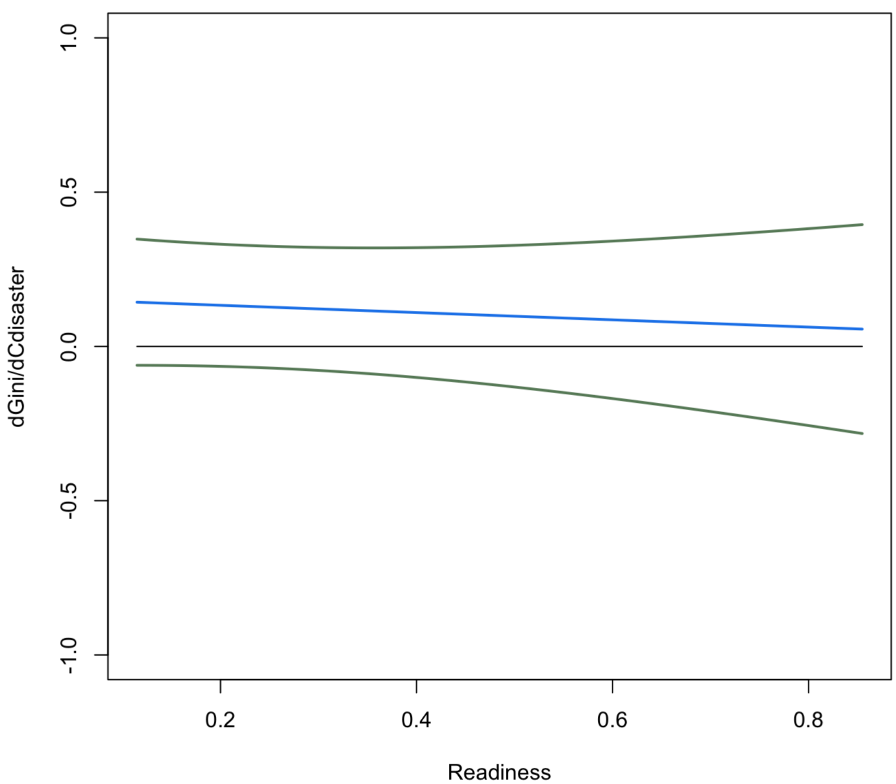

Figure 5: Marginal Effect of Cdisaster on Gini and 95% Confidence Intervals (Model 5)