Disaster Aid and Inequality:

An Analysis on Vulnerability and Development Outcomes in Post-Disaster Environments

Madison Kliewer

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1. Introduction

In 2010, a magnitude 7.0 earthquake hit Haiti, resulting in 222,570 dead and nearly 370,000 injured. What was more astonishing than the carnage, was the humanitarian response to such an event. The world rallied and pledged 13.5 billion dollars to help the Haitians rebuild and recover from the tragic event that hit their country. With such an influx of foreign aid, it would seem as though Haiti had the chance to "build back better." Yet after five years, people had not moved out of refugee camps, rubble was still on the ground, and the agriculture sector had not recovered due to the surplus of food donations that flooded in the market. An example like this elucidates the reality that the quantity of disaster aid does not translate to the quality of disaster recovery and therefore underscores the importance of effective aid in the recovery process.

This issue becomes even more pressing, given the evidence that nations with lower levels of development are at higher risk of natural disasters and experience worse disaster outcomes. A study by Tselios and Tompkins (2019) found that countries with lower levels of wealth and higher income inequality are associated with worse human and economic losses from disasters. A study by Ward and Shively (2017) empirically found that low-income countries are significantly more at risk of climate-related disasters, even after controlling for other exposures or possible confounding variables. These studies suggest that if disaster aid does not help nations to recover, it has the power to worsen development outcomes: both human and economic.

This evidence may shed light on the cycle of disasters, vulnerability, and destruction that is especially prevalent in the developing world. Observed on the national level, lower levels of development lead to worse disaster outcomes and higher disaster vulnerability. When a disaster strikes, development is worsened, leading to greater levels of disaster vulnerability. Given greater levels of vulnerability, a country is more likely to experience worse disaster outcomes, starting a cycle in which the next disaster is more harmful than before. This cycle is also observed on an individual level. Evidence suggests that disasters impact the poorest and most vulnerable people of a society, especially in countries with low wealth and high-income inequality (Pelling et al. 2004). Case studies in India and Mozambique solidify these findings, observing that the most vulnerable people in countries are hit the hardest by natural disasters and lack the resources to recover or to build resilience for future disasters (Duncan et al. 2017; Eriksen and Silva 2009).

Inequality is a driver of both national and household disaster vulnerability, as countries with higher inequality suffer worse outcomes, and more impoverished individuals are impacted disproportionately (Anbarci et al. 2005). Interestingly, Yamamura (2015) finds that natural disasters increase income inequality in the short term, although these effects disappear in the medium term. Therefore, it is of the utmost importance to understand disasters within the context of inequality and the role of aid in either helping or hindering these outcomes. Furthermore, according to the Intergovernmental Panel on Climate Change (2007), extreme weather events are becoming more frequent with the changing climate. There has been an increase in heavy precipitation events, tropical cyclone activity, and extreme weather events causing drought observed between 1970-2000. It becomes even more pressing to address the verity that disasters are a development issue, and take appropriate action to achieve the Sustainable Development Goals that call for the universal benefit of prosperity for all peoples, as outlined by the United Nations.

In this paper, I will study disaster aid and its role in disaster vulnerability. Primarily, I will be looking at the impact of disasters on inequality in developing nations and the subsequent influence of disaster aid to either mitigate or perpetuate these outcomes to gain insight into the drivers of disaster recovery and vulnerability. First, I will explore the relationship between disasters and human inequality in developing nations across the span of 6 years to understand the role of large disasters on short and medium-term inequality outcomes. Second, I will analyze if post-disaster aid will change the observed outcomes from disasters over the same period of 6 years. Finally, I will break down disaster aid by type to further understand disaster aid's impact on human inequality. In the next section, I review the current literature around the relationships between development, disasters, and aid. In section 3, I outline my data, and in section 4, I discuss my empirical methodology and underlying assumptions. Section 5 builds the conceptual model by tying together the results of relevant empirical studies and economic theory to build a hypothesis. Sections 6 and 7 discuss regression results, and section 8 concludes with contributions, and further research topics.

2. Review of the Current Literature

2.1 Disasters and Inequality

As noted previously, the data is clear that inequality is a driver of vulnerability. But what specifically makes nations with higher inequality suffer worse disaster outcomes? National inequality, defined as the distribution of economic variables such as wealth, health, and education, is an indicator of poverty. According to Karim et al. (2016), poverty is clearly associated with increased exposure to disaster-related hazards. One example of this is location, as the poor often reside in the most vulnerable areas, either in highly dense urban areas with unsafe buildings or in low productivity agricultural areas with little economic diversity. Both of these areas are highly vulnerable to natural disasters. Additionally, a case study following Hurricane Mitch in Nicaragua found that the hurricane did not affect productive asset ownership but adversely affected nonproductive asset holdings. This analysis concludes that the shock affected the poorest households disproportionately and suggested evidence of a geographical poverty trap (Jakobsen 2012).

Another aspect that could explain why the poor are disproportionately affected by disasters is occupation. According to a briefing paper by the Overseas Development Institute, the poorest members of society are often affected more by natural disasters. This is because they are more likely to be involved in occupations such as fishing and farming, industries that are adversely affected by natural disasters (ODI 2005).

Unfortunately, there are also longer-term adverse effects that disproportionately impact the poor. In response to shocks such as disasters, studies have observed that the most vulnerable members of societies resort to risk minimizing activities rather than income maximizing activities, and these actions produce adverse outcomes in the following years. A study that observed the effect of a drought-related loss of stature in preschool children in Zimbabwe concluded that lifetime earnings were 7% - 12% lower as a result (Alderman 2006). A meta-regression analysis by Karim et al. (2006) found evidence that in response to disasters, poor households smooth their food consumption by reducing their consumption of non-food items, specifically health and education. This reality becomes shockingly clear in a case study conducted by Anttila-Hughes et al. (2013) that looked at the post-typhoon infant mortality rates in the Philippines. The study concluded that “economic deaths,” defined as the disinvestment into human capital and health in response to disasters, account for 13% of overall infant mortality rate in the country.

It is clear that for a variety of reasons, unequal societies, and especially the poor, suffer the most severe adverse effects of a disaster, and these effects are likely to be much longer-lasting than initially thought.

2.2 Aid and Disaster Recovery

Where does aid fit into this picture? There have been a handful of studies that have observed the relationship between disaster relief and post-disaster outcomes. One such study conducted by Hochrainer (2009) observed the relationship between disaster relief and macroeconomic outcomes, finding that higher rates of aid reduce the negative impacts of disasters on GDP. Another study done by An et al. (2019) addresses how disaster aid may affect access to international capital, finding that emergency assistance from the international community can increase the access to capital and further promote recovery and growth. However, a case study looking at disaster aid after flooding in China found that emergency relief hindered economic growth, with implications that aid may impede recovery from a growth perspective (Xu et al. 2013).

At first glance, these studies imply that the general effects of disaster relief on wealth outcomes seem to be ambiguous. However, upon further investigation, the results make sense. Politically motivated donations could explain why the study observed positive effects of disaster aid on GDP. Disaster aid targets the recovery of the most productive assets. While this encourages technological change and weeds out unproductive firms in the recipient country, the assertion that aid increases wealth may overlook the potentially detrimental effect on inequality. While recovery favors productive firms, it ignores the fact that those who are poor are often poor because they have unproductive assets. The study found that aid deters growth would fit in line with the principle that aid disincentives recovery and could be targeted poorly for overall economic well being.

In terms of disaster aid and wealth distribution, a case study conducted in the wake of Hurricane Katrina found that increased levels of Federal Emergency Management Agency (FEMA) aid resulted in increased income inequality in the US (Howell et al. 2018). This paper suggests that FEMA aid targets recovering lost property, and only those who are wealthy enough to own property are recipients of aid. To my knowledge, there are no studies that observe the relationship between inequality outcomes and disaster aid across multiple countries.

2.3 Disaster Aid in Practice

It is crucial to understand what disaster aid achieves in practice to better understand where it may help or hinder inequality. There should be no question about the importance of initial relief for feeding and housing displaced people as well as providing medical services and search and rescue. However, certain aspects of disaster aid fail to address the overall recovery of a country. In a paper on disaster reconstruction and development, Margaret Arnold outlines disaster aid's aspects and where it falls short (2006). She notes that all too often, temporary relief becomes permanent, and the cycle of vulnerability continues. Many donors pull out during the recovery stage, leaving the country stuck in the temporary solutions put up during the relief stage. This is evident from the Haiti example previously discussed, where many people had not moved out of the temporary refugee camps that were erected right after the earthquake happened.

Another aspect of relief efficacy is coordination and community involvement. Given the sudden onset of disasters, response often favors speed rather than coordination, leaving an overabundance of some goods and services, while failing to address others. Additionally, the nature of a quick relief effort leads aid agencies to forgo community involvement, which is an integral part of delivering effective and targeted aid (Arnold 2006).

Unfortunately, aid donations are often politically motivated. Aid favors the donor rather than the receiver, in that the donor has the power to choose where their money goes, often in politically favorable ways. Arnold (2006) notes that housing recovery makes up over 50 percent disaster funds, as it is one of the most desirable activities for donor visibility. While this is an essential aspect of recovery, there is not enough attention given to the recovery of people's livelihoods (Arnold 2006).

Finally, aid may not be appropriately allocated to the poor. A study conducted in the wake of Hurricane Mitch in Honduras concluded that the primary determinant for receiving disaster relief was if one's dwelling suffered damages, with no association to pre-disaster levels of wealth (Morris 2003). This shows that in order to receive disaster aid, there is a required predisposition of wealth required, meaning that the most vulnerable and poor, who do not have dwellings, are overlooked.

Additionally, there may be longer-term impacts on development due to disaster relief. If the relief efforts stop at the temporary solutions, the adverse impacts on individuals will show up years after the event. Excess food donations could lower food prices and disincentivize workers to rebuild agriculture sectors hurt in the disaster, a theory that is further developed in section 4. A briefing by the Overseas Development Institute (2005) notes that donors respond to crises by reallocating funds and bringing forward commitments within existing multi-year programs, rather than providing new resources. Becerra et al. (2014) provide an empirical framework for this assumption, finding evidence of cross-sector allocation of humanitarian aid in response to disasters. All these aspects show that the adverse impacts of disaster aid may not be seen in the year after a disaster, but may take a few years to show up.

There is reason to believe that disaster relief, when done poorly, could have long-term consequences that do not help achieve development goals. My approach will look at the specific impacts that disasters and aid have on inequality and will break down aid by type to bring a broader understanding of how disaster aid affects the most poor and vulnerable members of a society.

3. Data

3.1 Disaster Data

Empirical papers that include disaster data almost exclusively rely on the Emergency Events Database (EM-DAT) maintained by the Catholic University of Louvain, Belgium. Disasters are defined as an event in which at least ten people died, one hundred people were affected, there was a state of emergency declared, or there was a call for international assistance. Disasters are grouped into either natural or technological disasters. Technological disasters are dropped for this analysis. Natural disasters are further identified by subgroups: geophysical, meteorological, hydrological, climatological, biological, and extra-terrestrial. Only geophysical (i.e earthquakes), meteorological (i.e storms), and hydrological (i.e floods) events are included in the dataset in order to capture the distinct impact of relief on sudden-onset disasters.

EM-DAT is an unbalanced database, as each natural or technological disaster is an observation in the data. In order to account for this, a disaster is defined as the sum of all disasters in a country for a given year for the remainder of the paper. Disaster severity measures are also included in the EM-DAT database, including the total number of people affected and killed, as well as total economic damages. For every observation, severity measures are aggregated for each country-year. Because this study observes the impact of disasters on the total population inequality, it would follow that a disaster killing 5,000 people would impact the national inequality of a small population more than a large population. To account for this, disaster severity is measured in per capita numbers, based on population data from the World Bank.

In order to observe the effect of 'large' disasters, and to avoid the overrepresentation of small disasters in the database, the definition of a large disaster is limited to be a country-year observation that had over the average number of deaths or affected in per capita measures (10.7 deaths per million inhabitants 6,529.1 affected per million inhabitants respectively).

3.2 Aid Data

For disaster relief data, two options provide data on post-disaster aid flows. One is the Financial Tracking Service from the United Nations (FTS), and the other is the Credit Reporting

System from the OECD's Development Assistance Committee (CRS). The FTS has a few advantages over the CRS dataset. First, it provides in-depth information on aid flows for specific events, making it possible to see flows for an individual disaster. Second, the FTS tracks a much broader scope of aid flows, including NGOs and large donors, while the CRS only includes aid flows from the 26 OECD countries and a few multilateral organizations. However, the FTS only tracks aid by voluntary reporting and therefore misestimates the actual amount of aid given. Due to this shortcoming, most empirical work that focuses on disaster relief uses the CRS data to get a more accurate estimate of new aid flows for a given country.

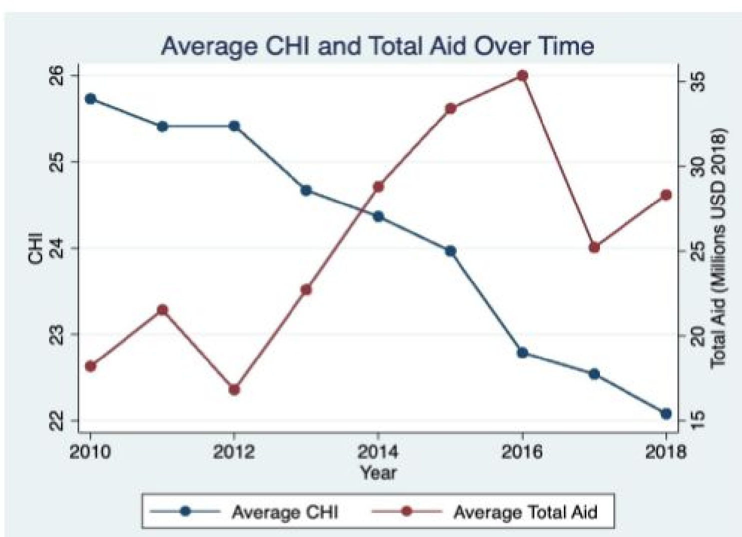
This analysis uses humanitarian aid flows from the CRS dataset. Specifically, disaster aid includes emergency relief flows, denoted as flow number 720 by the OECD, defined as humanitarian aid in response to an emergency caused by human-made crises and/or natural disasters, and reconstruction relief and rehabilitation flows, denoted by flow number 730, related to short term activities during and in the wake of disasters. Under the broad title of emergency response(720) , there includes material relief such as shelter and health supplies, food relief, and administration costs for organizing the relief effort. Under the title of reconstruction relief and rehabilitation (730), there are flows for the restoration of destroyed pre-existing infrastructure and social and economic rehabilitation to help people return to their previous livelihood or find a new one, as well as trauma treatment and counseling. Both of these flows are included to measure their impact both together and individually, as they may have different impacts on inequality.

3.3 Inequality Data

To measure the impact of disaster relief on the inequality, I used the Coefficient of Human Inequality (CHI) from the United Nations Development Programme. CHI is an index that measures inequality from a holistic viewpoint, as inequality is not sufficiently measured through income alone. It is an average computed by taking the unweighted average of education, health, and income inequalities. The data is already organized in country-year observations, starting from 2010 to 2018. The CHI is measured between 1-100, with lower scores indicating less inequality. The data lacks complete observations for every country in every year, therefore leading to an issue with coverage. Given the small number of years covered in the data, missing values were imputed by running a regression on CHI and year with country fixed effects, after dropping countries with more than three values missing. In total, 65 missing values were imputed, bringing the number of CHI observations from 835 to 900.

Figure 1

Average Total Aid and CHI Over Duration of Panel



Average coefficient of human inequality and total aid from the sample over the duration of the panel. Aid is measured in millions of 2018 USD and CHI is a composite score measured on a scale of 1-100, with a higher score meaning higher inequality.

4. Conceptual Model

To build the conceptual model and form a hypothesis, I will rely on microeconomic theory and assumptions based on the current literature around disaster aid. I assume that the post-disaster environment of the economy is perfectly competitive both in the short term and in the years following. I assume that disasters impact the market as a negative supply shock due to the sudden onset of the destruction of firms, agriculture, and fisheries, to name a few. For individual firms, I assume that disasters increase the average total cost, as recovery costs add to a firm's cost curve in the wake of a destructive natural disaster. I will now consider the impact of different types of emergency aid in the short and long term recovery of both the market and the individual firm.

4.1 Relief Aid

Relief aid, as defined by the humanitarian aid flow number 720 by the OECD's Creditor Reporting System, consists of medical supplies, food, and shelter in the immediate aftermath of an emergency event. I assume that the presence of relief aid is a positive supply shock, as it floods the market with food and supplies.

In the short run for the market, a disaster would shift the aggregate supply curve to the left, from point 1 to point 2 in Figure 2B. However, given the influx of relief aid, the supply curve will shift to the right, and the increase in supply may decrease the price level. This, combined with the already present increase in average total costs, will force firms with higher average total cost curves to shut down in the long run. Higher average costs mean greater inefficiency, which is associated with poverty. Therefore, I hypothesize that relief aid will increase inequality.

Figure 2

Individual Firm and Market Reaction to Relief Aid

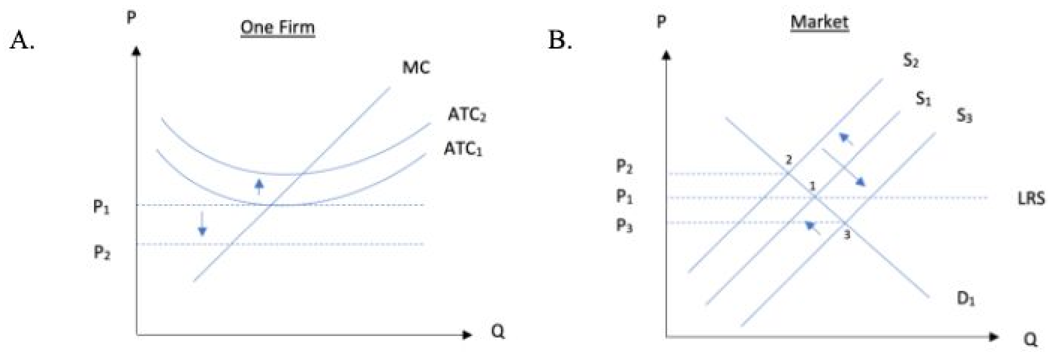


Figure A represents the single firm's supply curve, while figure B represents the market aggregate supply and demand in response to disasters and relief aid. In figure A, ATC will increase from the disaster and price will decrease from the positive supply shock due to relief aid in the short run. In the long run firms will shut down and supply will decrease, forcing prices to return to pre-disaster levels. In figure B, supply will shift from point 1 to point 2 due to the negative supply shock from the disaster, and will move to point 3 from relief aid in the short run. In the long run, supply and demand will return to point 1 as supply decreases with the exit of firms, eventually ending at the long run supply curve.

In the long run, individual firms will leave the market, decreasing aggregate supply back, eventually forcing the market to land on the long term supply curve. The economy will end up at the same place as the pre-disaster levels; however, the least efficient firms are forced to leave the market. Based on this, I hypothesize that an increase in relief aid will not affect short term inequality as it stops prices from increasing due to the supply shock, but will lead to greater inequality in the long run, as it favors the recovery of the most productive firms and inhibits the recovery of the least productive firms.

4.2 Reconstruction Aid

Reconstruction aid, defined by the humanitarian aid flow 730 from the OECD CRS data, includes the reconstruction of infrastructure as well as the social and economic recovery in the wake of a disaster. I assume that reconstruction aid does not affect aggregate supply or demand, but does impact the average total cost for individual firms. This is because reconstruction aid should not change the aggregate supply or demand of the economy but instead focuses on bringing the country and individual firms back to pre-disaster levels of infrastructure. For example, an influx of reconstruction aid may mitigate the increase of costs for an individual firm resulting from disasters, therefore allowing that firm to continue producing without the reconstruction costs.

In the short term, the market is hit by a negative supply shock triggered by the disaster, driving prices up. For an individual firm, the increase in average total cost is offset by the introduction of reconstruction aid, therefore returning the average total cost to pre-disaster levels. The increase in price will incentivize more firms to enter the market, therefore increasing aggregate supply.

In the long term, prices will return to pre-disaster levels on the long term supply curve, moving from point 2 to 1 on Figure 3B, therefore, returning both the market and individual firms to pre-disaster levels. Based on this theory, I hypothesize that the reconstruction aid will increase inequality in the short term, as it does not offset the increase of price level, but will not have any long term impacts on inequality.

Figure 3

Individual Firm and Market Reaction to Reconstruction Aid

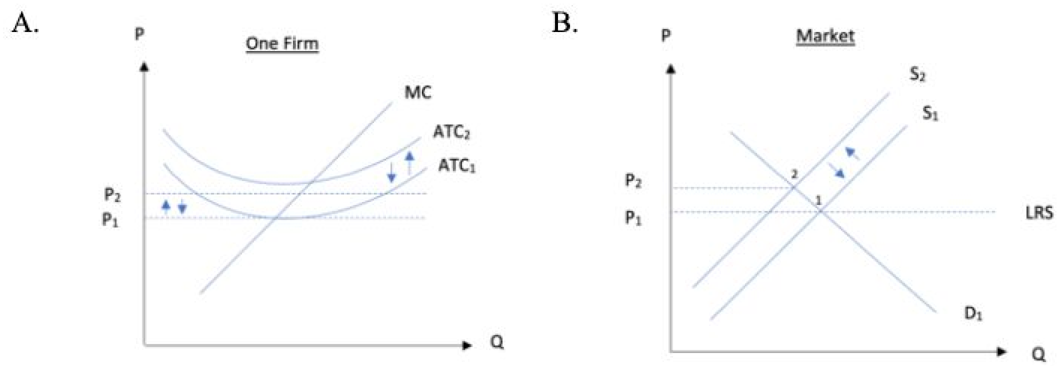


Figure A represents the single firm's supply curve, and figure B represents the market aggregate supply and demand in response to a disaster and reconstruction aid. In figure A, ATC increases from the disaster and will return to pre-disaster levels from reconstruction aid. Price will increase due to the negative supply shock in the short run, but will return to pre-disaster levels in the long run as firms enter the market as a result of a higher price level. In figure B, aggregate supply will decrease in the short run from the disaster moving from point 1 to point 2, but will return back to pre-disaster levels in the long run due to the increase of firms entering into the market, ending at the long run supply curve.

5. Econometric Specifications

Based on my hypothesis that disaster aid may impact inequality in the long run, I will be using panel data to run a lagged regression model with country and year fixed effects. The panel covers the years between 2010 and 2018 for all countries that are considered developing nations by the OECD and did not experience political emergencies during that time (100 countries total). The aid data also covers non-disaster emergencies. So, to account for flows that may not coincide with the presence of a disaster, countries that experienced political strife during the duration of the panel were dropped.[1] The descriptive statistics of the panel can be found in Table 1. A list of all countries included in the model can be found in Table 8.

I also assume that the treatment of aid is random. A handful of studies have observed the allotment of disaster aid, conclusively finding that severity of the disaster, country-specific aspects such as colonial ties, level of development, and distance, as well as media coverage all explain the distribution of aid following a natural disaster (Becerra et al. 2014; Strömberg 2007). When using country fixed effects, I can control for all country-specific properties that may influence aid distribution. Therefore, this leaves the severity of disaster and media coverage. According to a study by Eisensee et al. (2007), media coverage of an event favors the severity of the event itself, country-specific aspects, and the type of disaster. For example, they found that for every person that dies in a volcano, there must be 2000 more people who die in a drought to receive the same amount of aid. I am assuming that using country fixed effects will again control for this, as it allows my model to capture the random variation in severity of disaster present within a given country, and can also control for the likelihood of the type of disasters for a given country. I regressed measures of disaster severity on aid, with results found in table 2, showing that severity does explain aid distribution. Assuming that disasters follow the random fluctuations of nature, I can, therefore, assume that aid treatment is random.

No control variables are included in the model, again relying on the country and time fixed effects to control for the unobserved difference across countries invariant of time and across time, invariant of country. I first run a regression to observe the impact of the presence of

[1] These countries include Afghanistan, Iraq, Nigeria, Pakistan, Democratic Republic of the Congo, Republic of the Congo, Ethiopia, Sudan, Mali, Syria, Lebanon, Central African Republic, and Yemen. Haiti was dropped due to anomalous aid distribution.

a large disaster on inequality up to 5 years previous, controlling for level aid. The model is as follows:

$$CHI_{it} = \beta_1 Disaster_{it-5} + \beta_2 Disaster_{it-4} + \beta_3 Disaster_{it-3} + \beta_4 Disaster_{it-2} + \beta_5 Disaster_{it-1} + \beta_6 Disaster_{it}$$
$$\beta_7 Aid_{it-5} + \beta_8 Aid_{it-4} + \beta_9 Aid_{it-3} + \beta_{10} Aid_{it-2} + \beta_{11} Aid_{it-1} + \beta_{12} Aid_{it} + \delta_i + \delta_t + \varepsilon_{it}$$

in which *CHI* is the Coefficient of Human Inequality for country i, at time t, *Disaster* is a lagged dummy variable for if a country had a disaster according to the specifications outlined previously for country i, and year t, *Aid* is the natural log of total aid for country i, and time t, δ_i is the fixed effect that denotes the time-invariant, country-specific characteristics, δ_t is the fixed effect for time, invariant across countries, and ε_{it} is the error term.

In order to transition this model to observe the impact of disaster aid on inequality outcomes, aid is interacted with the disaster dummy in order to measure the aid for a country in which there was a coinciding large natural disaster for that year. This is to account for the fact that the aid data is measured not just for natural disasters, but also for man-made crises like war. My econometric model measuring the impact of total disaster aid on CHI is as follows:

$$CHI\ Total_{it} = \beta_1(Disaster_{it-5} \times Aid_{it-5}) + \beta_2(Disaster_{it-4} \times Aid_{it-4}) + \beta_3(Disaster_{it-3} \times Aid_{it-3})$$
$$+ \beta_4(Disaster_{it-2} \times Aid_{it-2}) + \beta_5(Disaster_{it-1} \times Aid_{it-1}) + \beta_6(Disaster_{it} \times Aid_{it}) + \delta_i + \delta_t + \varepsilon_{it}$$

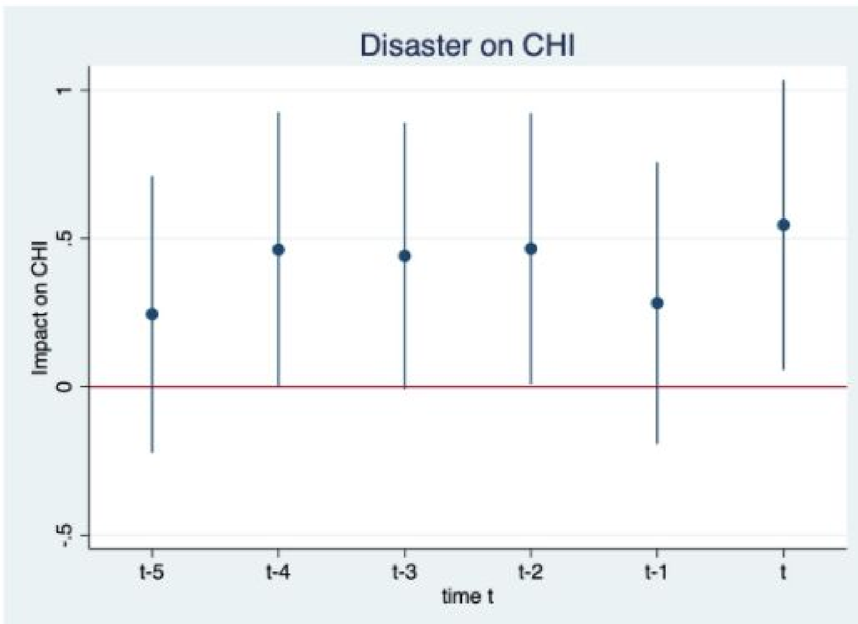
in which $Disaster \times Aid$ is the lagged interaction between the dummy variable for disaster and the natural log of total disaster aid for country i and time t.

6. Regression Results

6.1 Disasters on Inequality

Figure 4

Regression Results from the Presence of a Disaster on CHI, Controlling for Aid



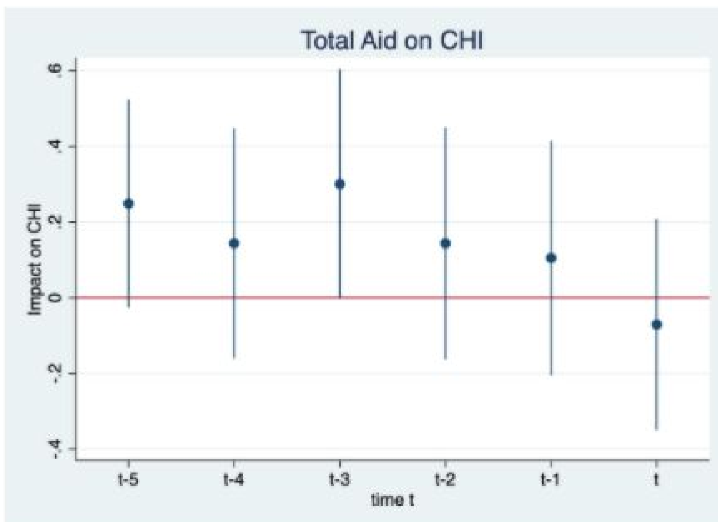
Regression results from observing the impact of 5 years of lagged disaster dummy variables on the coefficient of human inequality. Each value on the x-axis represents the regression coefficient for each independent variable included in the model. Each variable is the lagged dummy variable for presence of a disaster for a certain time t. The y-axis measures the predicted impact on CHI. Interpretation, for example, is if there was a large disaster 2 years ago, my model predicts that it would increase the current inequality by approximately .5.

Results from regressing the presence of a large disaster on inequality can be found in Figure 4 and Table 3. Results from this regression show that the presence of a large disaster (50th percentile of people killed or people affected) for a country-year is associated with an increase in inequality for up to 5 years following the event. These results suggest that disasters are inequality increasing events in the short to medium term, in line with the hypothesis that disasters drive inequality in the short run by adversely affecting the poorest and most vulnerable members of society, and that inequality is perpetuated into the medium term, perhaps by decisions made in the short run to adjust to the disaster shock.

6.2 Aid on Inequality

Figure 5

Impact of Total Aid on CHI Across 6 Years



Regression results from observing the impact on log total aid on the coefficient of human inequality. Each value on the x-axis represents the regression coefficient for each independent variable included in the model. Each variable is the lagged interaction between the dummy variable for presence of a disaster and the log of total aid for a certain time t. This will observe the impact of disaster aid on chi given there was a disaster. The y-axis measures the predicted impact on CHI. Interpretation, for example, is if there was a large disaster 2 years ago, my model predicts that for a percent increase in total aid, current inequality is predicted to increase by approximately .15.

Results from the regression of total aid interacted with disasters on inequality are in Figure 5 and Table 4. Interpreting the regression coefficients for a large disaster, a one percent increase in total aid response is associated with a decrease in human inequality in the year that disaster happened, and an increase in inequality in the year after the event and up to 5 years following. While the impact on CHI in the short term is not statistically significant, the results are significant in the medium term.[2] These results are not surprising, given that short term impacts will vary given the type of aid. However, these results could imply that total disaster aid will increase human inequality in the long term.

7. Breaking Down Aid

Not all types of aid will impact inequality outcomes the same, as discussed in greater detail in section 4. Given the ability to separate disaster aid by specific flow, I utilize this to further examine the impact of different types of disaster aid on inequality. The econometric specification for aid broken down by type is as follows:

$$
\begin{aligned}
CHI_{it} = {} & \beta_1(Disaster_{it-5} \times Rel_{it-5}) + \beta_2(Disaster_{it-4} \times Rel_{it-4}) + \beta_3(Disaster_{it-3} \times Rel_{it-3}) \\
& + \beta_4(Disaster_{it-2} \times Rel_{it-2}) + \beta_5(Disaster_{it-1} \times Rel_{it-1}) + \beta_6(Disaster_{it} \times Rel_{it}) \\
& + \beta_7(Disaster_{it-5} \times Rec_{it-5}) + \beta_8(Disaster_{it-4} \times Rec_{it-4}) + \beta_9(Disaster_{it-3} \times Rec_{it-3}) \\
& + \beta_{10}(Disaster_{it-2} \times Rec_{it-2}) + \beta_{11}(Disaster_{it-1} \times Rec_{it-1}) + \beta_{12}(Disaster_{it} \times Rec_{it}) + \delta_i + \delta_t + \varepsilon_{it}
\end{aligned}
$$

in which *Rel* is the natural log of relief aid for time t and country i, and *Rec* is the natural log of reconstruction aid for time t and country i.

Both relief and reconstruction aid are integral parts of the disaster recovery process, so it is therefore important to understand the balance of each type as a part of total aid, and understand how changing the mix may impact inequality. Therefore, my model that observes the mix of aid type is as follows:

$$
\begin{aligned}
CHI_{it} = {} & \beta_1(Disaster_{it-5} \times Percent\,Rel_{it-5}) + \beta_2(Disaster_{it-4} \times Percent\,Rel_{it-4}) + \beta_3(Disaster_{it-3} \times Percent\,Rel_{it-3}) \\
& + \beta_4(Disaster_{it-2} \times Percent\,Rel_{it-2}) + \beta_5(Disaster_{it-1} \times Percent\,Rel_{it-1}) + \beta_6(Disaster_{it} \times Percent\,Rel_{it}) + \delta_i + \delta_t + \varepsilon_{it}
\end{aligned}
$$

[2] Running an F test on the predictor variables for years t through t-2 results in an F value of .69 and a p value of .56, while the F test on predictor variables for years t-3 through t-5 results in an F-value of 4.63 and a p value of .0032

and

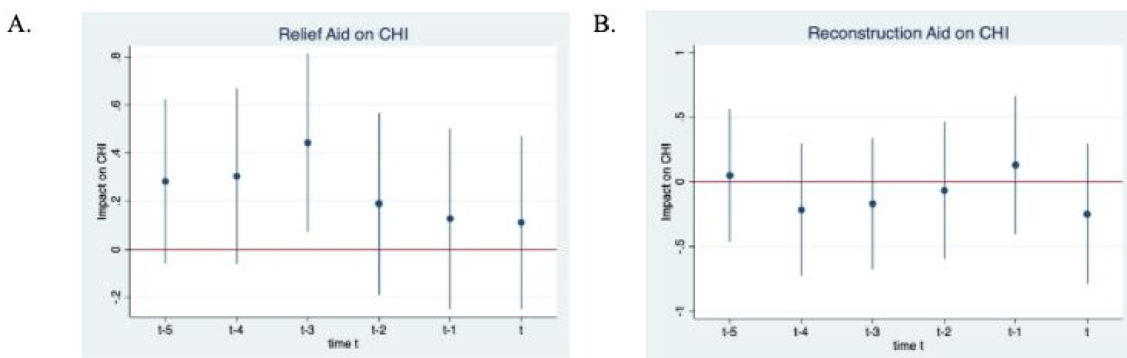
$$CHI_{it} = \beta_1(Disaster_{it-5} \times Percent\ Rec_{it-5}) + \beta_2(Disaster_{it-4} \times Percent\ Rec_{it-4}) + \beta_3(Disaster_{it-3} \times Percent\ Rec_{it-3}) + \beta_4(Disaster_{it-2} \times Percent\ Rec_{it-2}) + \beta_5(Disaster_{it-1} \times Percent\ Rec_{it-1}) + \beta_6(Disaster_{it} \times Percent\ Rec_{it}) + \delta_i + \delta_t + \varepsilon_{it}$$

in which *PercentRel* is the percent of relief aid out of total aid for country i, and year t, and *PercentRec* is the percent of reconstruction aid out of total aid for country i time t.

7.1 Relief vs Reconstruction Aid

Figure 6

Impact of Relief and Reconstruction on CHI



Regression results from the lagged aid broken down by type, on the coefficient of human inequality. Structure follows similarly to previous graphs, with the independent variables on the x-axis and the impact on CHI on the y-axis. Graphs A and B are from the same regression. Therefore interpretation would follow that if there was a disaster 2 years ago, a one percent increase in relief aid holding reconstruction aid constant is predicted to increase the CHI today by approximately .2.

Regression results from running five years of lagged disaster aid variables separated into relief aid and reconstruction aid on CHI can be found in Figure 6 and Table 5. A percent increase in relief aid in response to a disaster, holding the amount of reconstruction aid constant, is associated with an increased inequality for up to 5 years following the event. The results are not significant in the short term but are significant in the medium term.[3] These results, interpreted in the context of microeconomic theory, may imply that higher amounts of relief aid drive prices down and force inefficient firms to leave the market, making a significant impact on inequality in the medium term following an event. Regardless of theory, regression results suggest that an increase in relief aid is correlated with an increase in inequality in the medium term, implying that relief aid may cause worse harm than good. When looking at the results for reconstruction aid on CHI holding relief aid constant, there is no evidence to suggest an association between reconstruction aid and inequality in the short to medium term.[4] In the context of market and individual firms, this may show that the negative price shock from a disaster does not significantly impact inequality in the short term, and the targeted recovery of firms will stop the inequality increasing effects of the increase in total cost. Reconstruction aid may help to decrease the inequality increasing effects of disasters.

Results from the mix of aid type on inequality can be found in Figure 7 or Table 6. The results from both regressions lack significance in both the short and medium run, so the extent to which conclusions can be made is limited.[5] The most significant explanatory variable is the mix of reconstruction aid for time t-1. The interpretation would follow that a one percent increase in the mix of reconstruction aid in response to a large disaster is associated with an increase in inequality score by 1.5 for the year following the event. With some wariness, this could imply

[3] Running an F-test on relief aid variables for times t through t-2 results in an F-statistic of .82 and a p-value of .49, and the F-test on the relief aid variables for times t-3 through t-5 results in an F-statistic of 4.82 and a p-value of .0025.

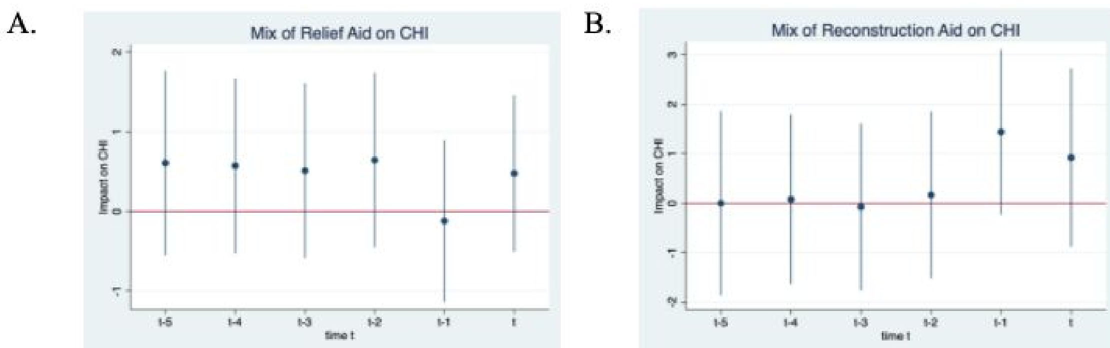
[4] F statistic for lagged reconstruction aid for times t through t-2 is .32 with a p-value of .81, and f statistic for reconstruction aid for times t-3 through t-5 is .47 with a p-value of .70.

[5] F statistic for lagged relief mix for time t through t-2 is .81 with a p-value of .49, and f statistic for times t-3 through t-5 is 1.59 with a p-value of .19. F statistic for lagged reconstruction mix for time t through t-2 is 1.30 with a p-value of .27, and f statistic for times t-3 through t-5 is 0.00 with a p-value of .99.

that favoring reconstruction aid over relief aid would result in short term inequality. Understanding this is the greater context of microeconomic theory, reconstruction aid targets long term recovery and ignores the immediate devastation that disasters produce. Therefore, overemphasis on reconstruction may result in short term inequality.

Figure 7

Impact of Aid Mix on Inequality



Regression results from the impact of the mix of relief aid and reconstruction aid as percent of total aid on the coefficient of human inequality. Structure follows similarly to previous graphs, with the independent variables on the x-axis and the impact on CHI on the y-axis. Interpretation would follow that if there was a disaster 2 years ago, for a percent increase of relief aid out of total aid for that disaster is predicted to increase CHI today by approximately .6.

8. Conclusion

This paper aims to better understand the role of disaster aid as a driver of disaster vulnerability and deveopment in developing nations. Utilizing panel data from 100 countries and aid data covering relief and reconstruction aid flows, my analysis allows me to make conclusions that may inform aid decisions moving forward.

First, disasters result in inequality in the short to medium term. This may be explained by the inability of low productivity firms to invest in disaster resilience or recover from the destruction caused by disasters. Additionally, evidence shows that households react to disasters by substituting health and human capital for food, which could drive inequality in the years following the event. There should be no question that disasters are an impediment to development, therefore there must be a greater emphasis on mitigating disaster destruction in order to achieve the Sustainable Development Goals outlined by the United Nations.

Second, total disaster aid is associated with an increase in inequality, most significantly during the 3 to 5 years after the event occurred. This implies that the observed instances of disaster aid may have had longer term negative impacts on inequality, therefore implying that the current distribution of post disaster aid may increase disaster vulnerability, perpetuate inequality, and not be in the best interest of development goals.

These serious implications underscore the reality that disaster aid must be critically analyzed. Relief aid is associated with an increase in inequality, especially in the medium term. This may be due to the nature of this type of aid, which is not intended to help a country recover, but rather seeks to alleviate the initial damages experienced after a disaster. While a world without disaster aid may result in much graver economic and human impacts, it does bring into question the very nature of post-disaster aid itself.

While this paper examines many aspects of the interaction of disaster aid on human inequality, many questions still remain open ended. Do the results found in this paper persist into the long run? What specific aspects about relief aid cause inequality? Would we reach the same conclusions when observing multi-year aid flows after the event? Answering these questions may help us come closer to addressing disaster recovery as a development issue and target disaster aid to be vulnerability reducing and resilience building.

So where does this land us? Disaster aid plays an important role in the recovery of a disaster, however, these necessary costs may play a part in perpetuating poverty and increasing disaster vulnerability. My findings stress the importance of placing more emphasis on disaster risk prevention to promote sustainable development and lessen the losses from disasters. Given the reality that climate related disasters are more frequent, this call has never been more urgent.

Table 1: Descriptive Analysis

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
CHI	900	24.11	8.868	6.300	46.30
Total Deaths	425	217.0	851.8	1	9,034
Total Affected	502	1.639e+06	9.702e+06	5	1.457e+08
Total Deaths per Capita	425	4.67e-06	1.91e-05	1.51e-08	0.000334
Total Affected per Capita	502	0.0185	0.0604	1.85e-07	1.051
Total Aid	900	25.59	69.40	0	522.2
Reconstruction Aid as % of Total	793	0.132	0.255	-0.163	1
Relief Aid as % of Total	793	0.868	0.255	0	1.163
Total Aid (ln)	900	1.603	1.655	0	6.260
Relief Aid (ln)	900	1.508	1.615	0	6.224
Reconstruction Aid (ln)	900	0.445	0.888	-0.109	5.547

Table 2: Regression Results on Disaster Severity and Aid

VARIABLES	(1) Total Aid	(2) Total Aid	(3) Total Aid (ln)	(4) Total Aid (ln)
Total Deaths	0.0109***		0.000134**	
	(0.00348)		(5.41e-05)	
Total Affected	-4.59e-08		1.45e-08***	
	(3.35e-07)		(5.20e-09)	
Total Damages ‘000 USD	6.88e-07	-6.56e-08	2.97e-08**	9.42e-09
	(7.86e-07)	(8.13e-07)	(1.22e-08)	(1.27e-08)
Total Deaths per Capita		321,707*		241.5
		(169,187)		(2,646)
Total Affected per Capita		319.6**		9.209***
		(125.4)		(1.961)
Constant	23.21***	17.32***	1.873***	1.751***
	(3.711)	(4.263)	(0.0576)	(0.0667)
Observations	213	213	213	213
R-squared	0.086	0.137	0.184	0.219
Number of Countries	67	67	67	67

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Regression Results on the Presence of a Large Disaster on CHI, Controlling for Aid

VARIABLES	(1) CHI
$Disaster_{t-5}$	0.244
	(0.238)
$Disaster_{t-4}$	0.463*
	(0.236)
$Disaster_{t-3}$	0.441*
	(0.229)
$Disaster_{t-2}$	0.466**
	(0.233)
$Disaster_{t-1}$	0.282
	(0.242)
$Disaster_{t}$	0.546**
	(0.249)
Total Aid $(ln)_{t-5}$	0.227*
	(0.134)
Total Aid $(ln)_{t-4}$	0.0230
	(0.155)
Total Aid $(ln)_{t-3}$	0.166
	(0.153)
Total Aid $(ln)_{t-2}$	-0.0860
	(0.151)
Total Aid $(ln)_{t-1}$	0.0158
	(0.151)
Total Aid $(ln)_{t}$	-0.201
	(0.134)
Constant	23.32***
	(0.347)
Observations	900
Number of Countries	100
R-squared	0.031

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regression Results of Total Aid on CHI

VARIABLES	(1) CHI
Total Aid (ln)$_{t-5}$	0.277*
	(0.148)
Total Aid (ln)$_{t-4}$	0.159
	(0.161)
Total Aid (ln)$_{t-3}$	0.319**
	(0.161)
Total Aid (ln)$_{t-2}$	0.140
	(0.163)
Total Aid (ln)$_{t-1}$	0.132
	(0.165)
Total Aid (ln)$_{t}$	-0.0367
	(0.150)
Constant	23.78***
	(0.332)
Observations	900
Number of Countries	100
R-squared	0.040

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Regression Results of Reconstruction and Relief on CHI

VARIABLES	(1) CHI
Relief Aid $(\ln)_{t-5}$	0.281
	(0.175)
Relief Aid $(\ln)_{t-4}$	0.304
	(0.187)
Relief Aid $(\ln)_{t-3}$	0.443**
	(0.189)
Relief Aid $(\ln)_{t-2}$	0.189
	(0.193)
Relief Aid $(\ln)_{t-1}$	0.127
	(0.192)
Relief Aid $(\ln)_{t}$	0.111
	(0.184)
Reconstruction Aid $(\ln)_{t-5}$	0.0448
	(0.263)
Reconstruction Aid $(\ln)_{t-4}$	-0.216
	(0.261)
Reconstruction Aid $(\ln)_{t-3}$	-0.170
	(0.258)
Reconstruction Aid $(\ln)_{t-2}$	-0.0667
	(0.270)
Reconstruction Aid $(\ln)_{t-1}$	0.129
	(0.272)
Reconstruction Aid $(\ln)_{t}$	-0.250
	(0.277)
Constant	23.59***
	(0.339)
Observations	900
Number of Countries	100
R-squared	0.050

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regression Results of Mix of Relief and Reconstruction on CHI

VARIABLES	(1) CHI	(2) CHI
Percent Relief$_{t-5}$	0.801	
	(0.614)	
Percent Relief$_{t-4}$	0.703	
	(0.574)	
Percent Relief$_{t-3}$	0.618	
	(0.575)	
Percent Relief$_{t-2}$	0.716	
	(0.576)	
Percent Relief$_{t-1}$	-0.0585	
	(0.532)	
Percent Relief$_{t}$	0.548	
	(0.514)	
Percent Reconstruction$_{t-5}$		-0.0664
		(0.967)
Percent Reconstruction$_{t-4}$		0.0460
		(0.888)
Percent Reconstruction$_{t-3}$		-0.0667
		(0.877)
Percent Reconstruction$_{t-2}$		0.166
		(0.875)
Percent Reconstruction$_{t-1}$		1.463*
		(0.866)
Percent Reconstruction$_{t}$		0.931
		(0.935)
Constant	23.73***	24.81***
	(1.216)	(0.199)
Observations	708	708
R-squared	0.029	0.013
Number of Countries	89	89

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: List of Countries in Panel

Countries	
Angola	Liberia
Albania	Saint Lucia
Argentina	Sir Lanka
Armenia	Lesotho
Azerbaijan	Morocco
Burundi	Moldova
Benin	Madagascar
Burkina Faso	Maldives
Bangladesh	Mexico
Bosnia and Herzegovina	Macedonia
Belarus	Montenegro
Belize	Mongolia
Bolivia	Mozambique
Brazil	Martinique
Bhutan	Mauritius
Botswana	Malawi
Chile	Namibia
China	Niger
Côte d'Ivoire	Nicaragua
Cameroon	Nepal
Columbia	Panama
Comoros	Peru
Cape Verde	Philippines
Costa Rica	Paraguay
Djibouti	Palestine
Dominican Republic	Rwanda
Ecuador	Senegal
Egypt	Slovenia
Gabon	El Salvador
Georgia	Serbia
Ghana	Sao Tome and Principe
Guinea	Suriname
Gambia	Swaziland
Guinea-Bissau	Chad
Guatemala	Togo
Guyana	Thailand
Honduras	Tajikistan
Croatia	Turkmenistan
Haiti	Timor-Leste
Indonesia	Tunisia
India	Turkey
Iran	Tanzania
Jamaica	Uganda
Jordan	Ukraine
Kazakhstan	Uruguay
Kenya	Venezuela
Kyrgyzstan	Viet Nam
Cambodia	South Africa
Kiribati	Zambia
Laos	Zimbabwe

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