# Online Appendix: Do Voters Value Relief over Preparedness? Evidence from Disaster Policies in Malawi

## Contents

# A Details: Previous Evidence

Healy and Malhotra (2009) show that citizens reward incumbents for relief but not prevention spending. In particular, the study only finds a significant association between incumbent vote share and relief transfers to individual voters but not for collective relief or prevention. Cavalcanti (2018) finds similar evidence studying droughts in Brazil. While voters rewarded the President's party for relief spending and preparedness spending after a drought, the former effects are larger in magnitude and more robust to different specifications. This suggests that voters are less likely to reward previous preparedness even when a disaster subsequently happens. The paper also shows that voters are more likely to vote for an incumbent mayor aligned with the central government, arguing that voters do so because they expect better access to private relief transfers. Several studies support the proposition that voters reward incumbents for relief spending. Gallego (2018) finds tentative evidence that local mayors in Colombia used the increased influx of aid after a disaster to target relief spending in the forms of private transfers and local public goods to buy votes. However, the study only finds significant effects for private transfers. Gasper and Reeves (2011) and Cole, Healy, and Werker (2012) show that voters punish politicians less for natural disasters if they provide effective disaster relief. Bechtel and Hainmueller (2011) find that the positive effects of relief spending can last several years. In line with these findings, Cooperman (2022) observes that Brazilian mayors issue drought declarations, triggering relief payments, in the run-up to elections. However, Gailmard and Patty (2019) have shown formally that voters would reward relief efforts over prevention efforts if they were uncertain about the effectiveness of prevention. In their model, prevention spending is a bad signal for voters about the quality of politicians because voters are less informed than politicians about the need for prevention and because politicians can be "corrupt" in the sense that they can privately benefit from prevention spending. This paper finds empirical evidence that supports this view. Voters seem to have more pessimistic expectations about the effectiveness of preparedness efforts compared to relief efforts, leading them to value relief efforts over preparedness efforts. However, voters value effective prevention similar to effective relief. While this paper remains agnostic about the sources of the pessimistic expectations, I find no evidence they are driven by the corruption of politicians.

# B Background: Malawi

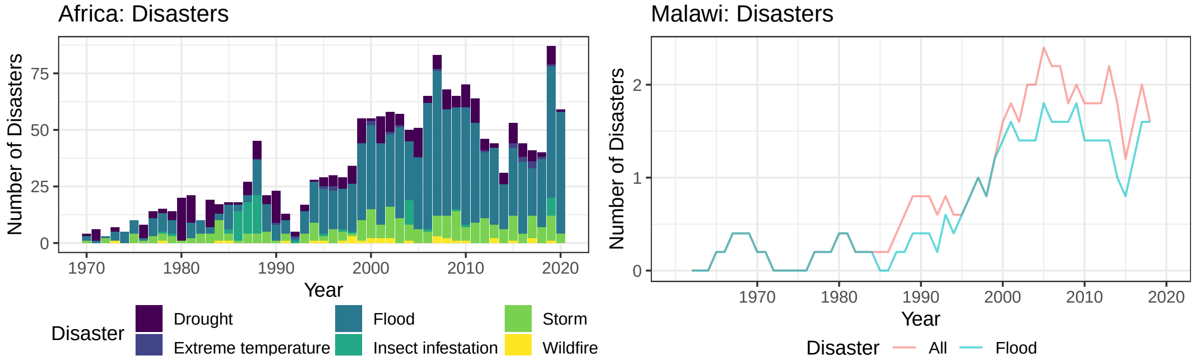
## B.1 Sample Region

Regions within Malawi are rather ethnically homogenous; Chikwawa and Nsanje are part of the Sena region (Robinson 2016).

## B.2 Natural disasters: Temporal Variation

As we can in the left panel of Figure 1, the numbers are driven by typhoons and floods that often hit the coastal areas. Malawi is a typical case in the region and frequently suffers from floods, droughts, and harvest failures. With a total of 51 disasters between 1970 and 2020, Malawi ranks 12 out of 55 countries in the data. Pauw et al. (2011) use data prior to 2010 and estimate that at least $1,7\%$ of Malawi's gross domestic product (GDP) is lost yearly because of droughts and floods.

Figure 1: Natural Disasters across Africa 1970-2020




*Notes: data from Guha-Sapir and Hoyois (2015).*

### B.3 Natural disasters and Disaster Preparedness: Geographic Variation

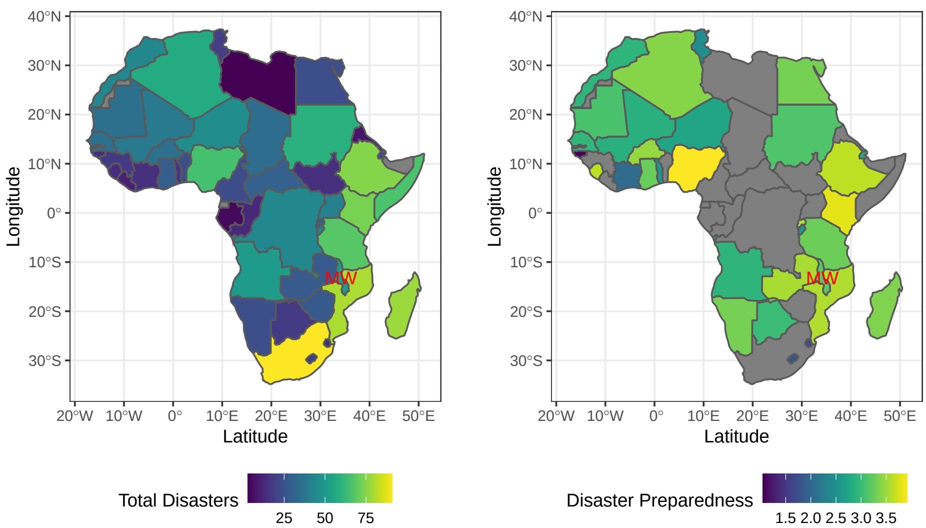
#### B.3.1 Data Source:

HFA National Progress; an indication of capacities to deal with climate-related nature disasters. This indicator uses monitoring from the Hyogo Framework Action (HFA). The HFA outlined an action plan from 2005 to 2015 to establish five priorities for disaster preparedness. Countries are monitored in two-year intervals against the five priorities by self-reported data.

#### B.3.2 Notes:

(1) HFA action plan was outlined in 2005 and the reports were not made until 2007, therefore, disaster preparedness was not tractable before that for all countries. (2) The self-reported data are not always comparable among countries. However, the HFA report still provides so far the most comprehensive data set that monitors the progress of capacity building in terms of preparing for natural disasters.

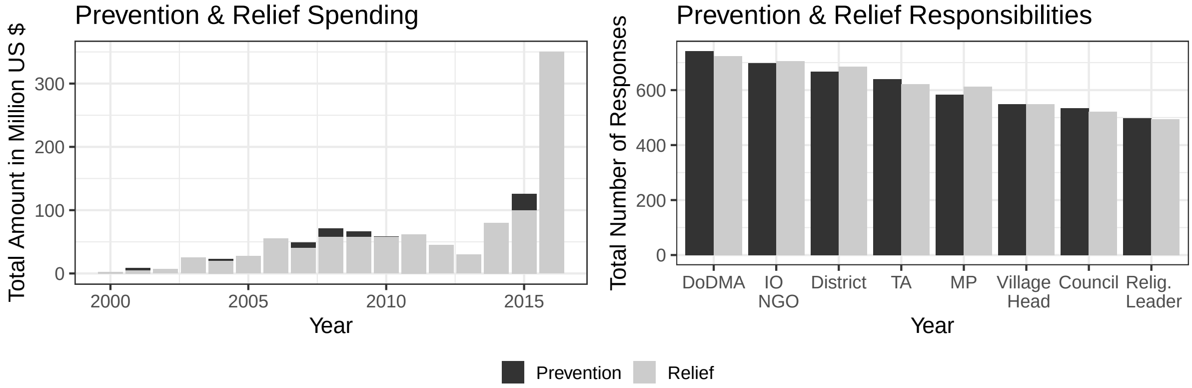
Figure 2: Number of Natural Disasters by Country (1970 and 2020) and Preparedness by Country (2007-2011).




*Notes: Left Panel: Total number of natural disasters by country, (Guha-Sapir and Hoyois 2015). Location of Malawi is marked with MW. Right Panel: Data from the Adaptive Capacity Indicator 2 on disaster preparedness (average of 2007, 2009, 2011) from the Notre Dame Global Adaptation Initiative (ND-GAIN) (Chen et al. 2015).*

### B.4 Prevention and Relief spending: Malawi

Figure 3: Malawi Disaster Spending and Perceived Responsibilities




*Notes: Left Panel: relief aid spending (2000-2016) is based on data from the National Resilience Strategy Report. Prevention aid spending (2000-2015) was based on data from Peratsakis et al. (2012). Year refers to date when the aid agreement was signed Right: Perceived Responsibilities; own survey data collected 2018; Based on the question: "In your opinion, which actors are responsible for disaster response and relief?" The graph displays the sum of respondents who chose "very responsible" for a given actor.*

### B.5 Perceived political responsibilities: Malawi

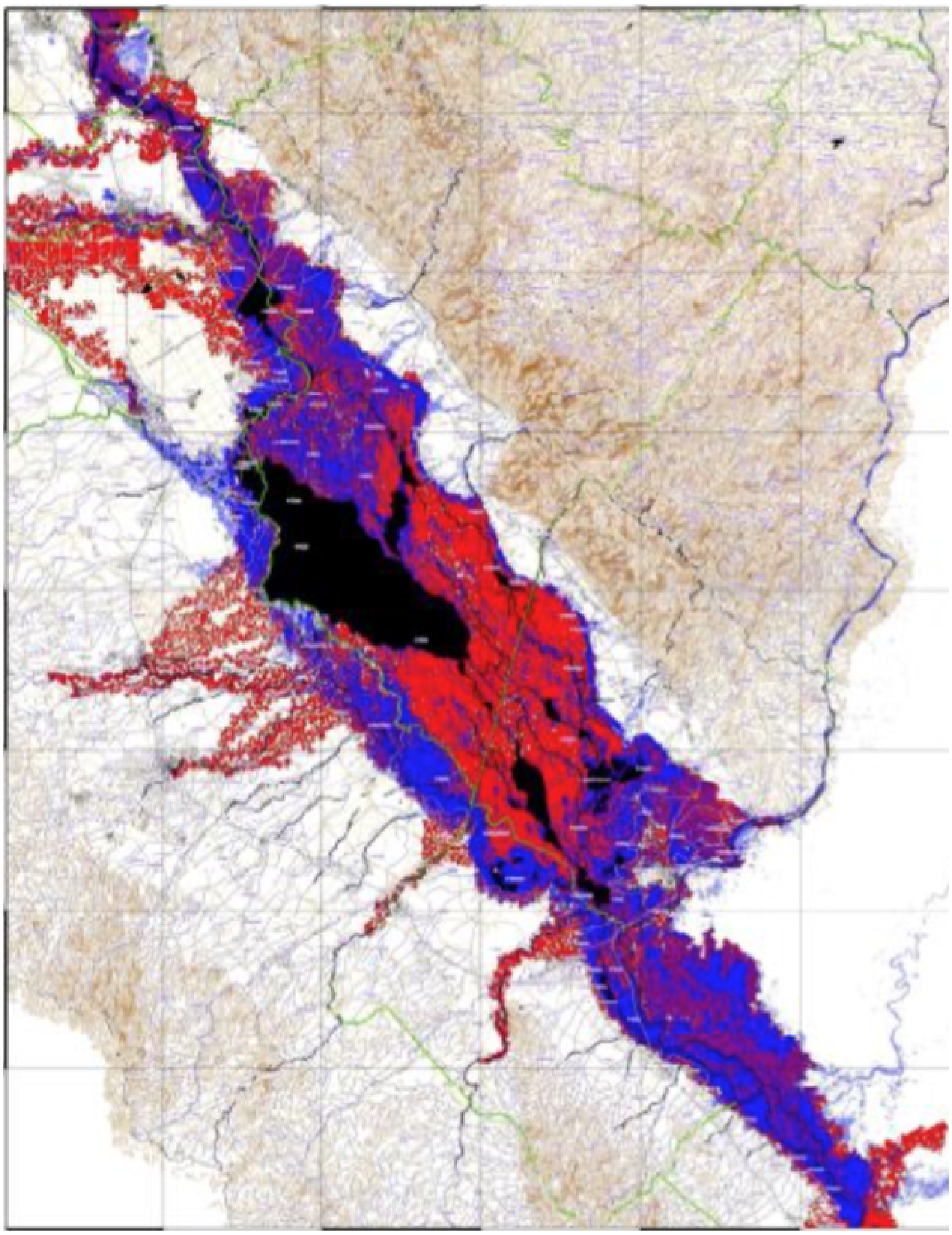
Malawi is divided into 28 districts, each administered by a district council under the direction of a district commissioner appointed by the president. Each district council consists of elected councilors (one for each ward within the district), members of parliament (MPs), ex-officio members, and chiefs (traditional authorities-TA's). While the formal responsibility for the provision of local public goods lies also with district councils (Chinsinga 2005), MPs play a key role in providing local public goods, both formally and informally. Since 2006, MPs have had discretion over constituency development funds to implement development projects in their district (Ejdemyr, Kramon, and Robinson 2018).

The lower right panel of Figure 3 depicts survey evidence on various actors' perceived responsibility for disaster prevention and relief. In line with the expectations, most respondents see DoDMA as responsible, followed by the district commissioner, traditional authority, and MPs. Notably, international organizations and NGOs are the second most popular category. This is not surprising, given respondents also noted that most of the help came from international donors, followed, by a wide margin, by DoDMA, MPs, and the district commissioner (see Figure 6).

## B.6 Background Flood 2015

In 2015, the region experienced the highest seasonal rainfall ever recorded, damaging about 89,000 hectares of land and 500,000 houses, affecting 1,000,000 people, leaving 230,000 displaced, and killing 106. The flood led to massive destruction of crops, devastated agricultural production, and destroyed social infrastructure – specifically, schools, health facilities, and housing (PDNA-Report 2015). In the aftermath of the 2015 floods emergency plans were widely discussed (The Nation 2015).

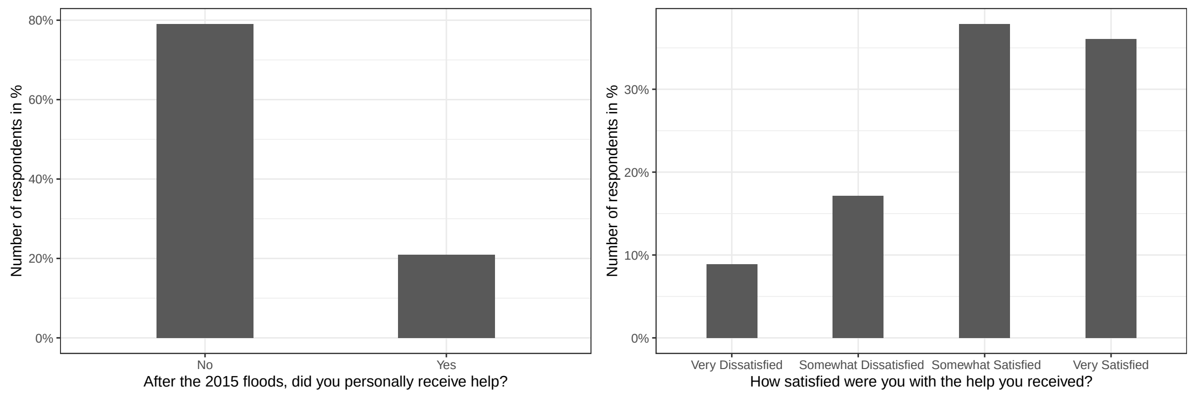
Figure 4: Blue color presents the actual floods, and red color represented the modelled floods based on prior data. Black color represents permanent water bodies. Source: PDNA-Report (2015).



## B.7 Help received during 2015 flood and satisfaction with response

Evidence from the survey suggests that respondents believe that the relief allocated to them previously was effective. The survey asked respondents, after the conjoint experiment, if they had received relief following the 2015 floods, from whom, and how satisfied they were with the help they received. While the subjective satisfaction with previous relief might not be an ideal predictor for the actual effectiveness of relief funds (for example, because it does not measure optimal allocation across households or communities), for the conjoint, it would only be important that respondents perceive relief funds as an effective means to alleviate destruction from the disaster. Therefore, satisfaction with previous relief should be sufficient.

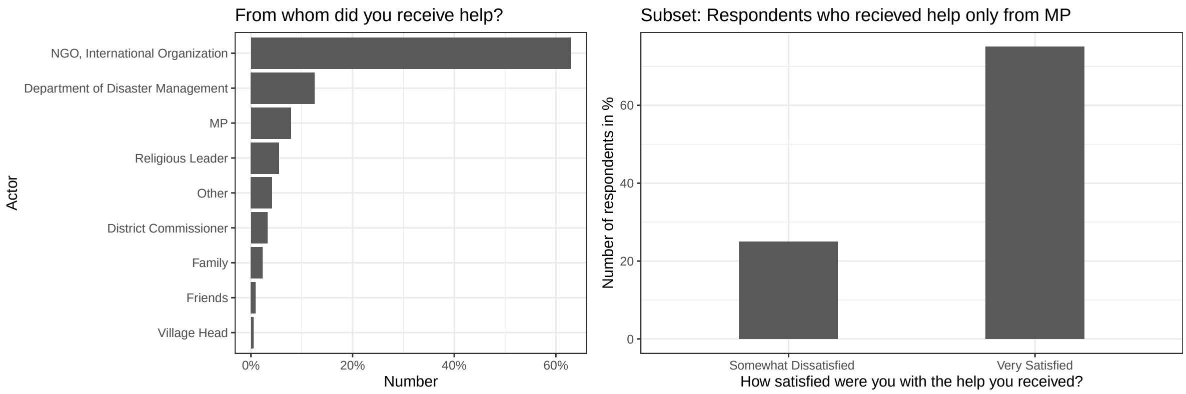
Figure 5: Help received after the 2015 flood (left) and satisfaction with response (right)




*Notes*: data from original survey

The left plot of Figure 5 shows that only a minority of respondents (20%) state that they received help. However, the right plot reveals that among those who did receive help, the majority were overwhelmingly satisfied with it. The left plot in Figure 5 further indicates that respondents mostly received help from international donors and NGOs (multiple answers were possible, and most respondents named more than one source of help). However, approximately 10% also received help from their MP. While only a handful of people exclusively received help from their MP, those who did were very satisfied, as seen in the right plot of Figure 6. The high satisfaction rates among those who received aid indicate a successful translation of donated funds into meaningful assistance.

Figure 6: Actors help received (left) and satisfaction when received help only from MP (right)




*Notes*: data from original survey

# C Changes to the Pre-Analysis Plan

## C.1 Theory Development: Pessimistic Expectations about Preparedness

The theory regarding voters' pessimistic expectations about the effectiveness of preparedness efforts and the associated hypotheses (H1a, H1b, H2) were developed after the study was conducted. These hypotheses were not part of the original pre-analysis plan, which focused on broader voter preferences for disaster response and preparedness policies. The new hypotheses emerged as a result of conceptual thinking informed by the observed behavior during the experiment, suggesting that voter perceptions of preparedness are driven by expectations about its effectiveness. The new hypotheses are as follows:

- $H_{1a}$: Voters will be more likely to support incumbents for relief efforts than for prevention efforts.
- $H_{1b}$: Voters will be indifferent between incumbents who provide effective relief and incumbents who provide effective prevention.
- $H_2$: Voters will be more likely to support incumbents for preparedness efforts if the incumbents have no record of corruption.

## C.2 Exploratory Analysis: Marginal Effect of Preparedness Conditional on Effectiveness

In addition to the new hypotheses, I conducted an exploratory analysis to further investigate the theory of pessimistic expectations. Specifically, I tested the marginal effect of preparedness efforts conditional on observed effectiveness. This test was not pre-registered but was added to better understand the emerging pattern that voters' support for preparedness efforts increases when they observe repeated success in mitigating disaster damages. This analysis complements the new theoretical framework developed after observing the data patterns.

## C.3 Additional Changes

There were also minor deviations from the pre-analysis plan in the naming of attributes. For example, the attribute labeled "Visit" in the final analysis was originally called "Emotional Intelligence" and was categorized under "Competence" in the pre-analysis plan. This change was made to reflect the specific behavior of visiting a disaster site, which was more relevant to the study context.

## C.4 Pre-Registered Hypotheses and Tests

The pre-registered hypotheses (see Pre-Analysis here: https://osf.io/6cvzh) were centered around the effects of economic distress on voter preferences for disaster response and preparedness policies. Specifically, the pre-registered hypotheses were as follows:

- **Hypothesis 1**: Voters primed for economic hardship will be more likely to vote for candidates that deliver material benefits.
- **Hypothesis 2**: Voters primed for economic hardship will be more likely to vote for candidates that use vote buying.

These hypotheses were tested and the results can be found in Section J.

# D Ethics

This research seeks to maximize welfare for Malawian society while minimizing risk to participants in the study. The survey and conjoint experiment asked participants about their experience with natural disasters and preferences for natural disaster policies. Given the sensitivity of natural disasters, ethical questions concerning the participants and study team were important.

## D.1 Impacts on Political Processes

The conjoint experiment was designed with reference to actual disaster policies from the political context. However, the scenarios were explicitly hypothetical. The main objective was to measure voter preferences and beliefs and not to influence those. Therefore, I do not expect any impacts on the political processes.

## D.2 Trauma and Harm

I tried to minimize and monitor the risk of re-traumatization. Because the study was focused on the economic consequences of natural disasters, I shortened a standard disaster questionnaire and only included relevant questions. Legerski and Bunnell (2010) reviewed literature on participation in trauma-focused research. They conclude that most studies have found that only a minority of participants experienced distress. However, the negative effect disappeared quickly over time, and a majority of participants experienced their participation as positive and beneficial to society.[1] Another concern is that the disaster prime might have induced psychological harm. However, this concern is ameliorated because of two reasons. First, the disaster prime was hypothetical and did not reference past events. Second, to monitor re-traumatization due to the disaster prime, I included a battery of questions on psychological well-being. I found no evidence that the prime induced psychological harm to participants. Therefore, I expect that there was minimal, if any, physical, psychological, social, and economic harm to research subjects, assistants, or staff. Lastly, I expect the broader social impacts of the research process to be net positive, as they allow me to inform policymakers about citizen preferences and beliefs about natural disaster policies.

## D.3 Institutional Review

The survey questionnaire was reviewed and approved by the Malawi Institutional Review Board (IRB) via the Institute of Public Opinion Research (IPOR), Malawi. The review by a Malawian board helped to ensure that the survey did not violate any local norms. In addition, this research followed the Swedish Data Services regulations and guidelines for research ethics.

## D.4 Invitation and Compensation

The enumerators from IPOR were experienced professionals who had conducted interviews in Malawi before. Participation in the survey was completely voluntary, and participants were not offered any compensation. I did not offer any financial incentives to participate in the study because it might have pressured on respondents.

## D.5 Informed Consent

Informed consent was sought at the initial contact with potential participants. Interviews for the survey began with an introduction to the project and assurances of confidentiality. Specifically, the script read: "*Good day. My name is [name of enumerator]. I am from the Institute of Public Opinion and Research, which is working with [Name of the Univsersity]. I do not represent the government or any political party. We are studying the views of citizens in Malawi about how the country is governed and the quality of life in your area. We would like to discuss these issues with you. Your answers will be confidential. They will be put together with other people we are talking to, to get an overall picture. It will be impossible to pick you out from what you say, so please feel free to tell us what you think. There is no penalty for refusing to participate. Do you wish to proceed?*" The consent was obtained orally. Oral consent is most appropriate in Malawi because much of the rural population is illiterate and the provision of written documents can cause unnecessary confusion and stress to participants. The interviews proceeded only after getting the consent of potential participants.

[1] The authors did note, however, that participants typically self-selected into studies which could have induced bias.

### D.6 Deception

As the survey included a conjoint experiment, randomly selected subgroups of the sample were presented with different disaster policies of candidates. Yet these statements constituted no deception: they were explicitly hypothetical and constructed with reference to politicians' actual policies in the context.

### D.7 Data

All data collected is kept anonymous and stored in encrypted files. I do not distribute any data with names or GPS coordinates. All data is retained on encrypted servers.

# E Questionnaire

## E.1 Background Characteristics

1. IDNUM: Questionnaire number
2. Geo-code: Longitude/Latitude
3. ENUMERATOR: NAME
4. Based on your impression of the respondent's household, estimate the financial standing of households in that locality:
   <1> Low income
   <2> Middle income
   <3> Upper-middle income
   <4> High income
5. Gender of the person who opened the door:
   <1> Male
   <2> Female
   <98> Unknown
6. How old are you?
   ... years
7. Did you live in this community in 2015:
   <1> Yes
   <2> No
   <98> Don't want to answer
8. What is your highest level of education?:
   <1> No formal schooling
   <2> Informal schooling only (including Koranic schooling)
   <3> Some primary schooling
   <4> Primary school completed
   <5> Intermediate school or some secondary school/high school
   <6> Secondary school/high school completed
   <7> Post-secondary qualifications, other than university
   <8> Some University
   <9> University completed
   <10> Post-graduate
   <98> DK/RA

## E.2 Community Project Participation

- Do you and your neighbors help each other with...?
  1. Ensuring security by helping solve disputes or keeping the neighborhood safe from crime.
  2. Participating in local development projects (building roads, building schools and clinics).

  <0> No <1> Yes

- In general, do you and your neighbors help each other on a daily, weekly, monthly, less than monthly basis? (Which is closest?) <1> Less than monthly <2> Monthly <3> Weekly <4> Daily

- In the last year, have you (personally) met with any of the following groups in order to discuss potential solutions to community problems?

  1. Your neighbours and friends.
  2. A wealthy/influential local family.
  3. Any CSOs, such as trade unions, professional associations, business organizations or others.
  4. Members of your Church, Mosque or other religious organization.
  5. Members of a political party or parties.

  <0> No <1> Yes

### E.3 Trust

- For each of the following, please tell me whether you trust them very much, trust them somewhat, distrust them somewhat, or distrust them very much to work for your interests?

  1. Your Traditional Authority
  2. Your village head
  3. Your religious leader
  4. Your member of parliament
  5. Your local council member

  <1> Distrust very much <2> Distrust somewhat <3> Trust somewhat <4> Trust very much

- If one accepts money, gifts, or food from a candidate, is he or she obligated to vote for this candidate?

### E.4 Psychological Wellbeing

The next questions are about how you have been feeling during the past 30 days.

- About how often did you feel tired out for no good reason?
- About how often did you feel nervous?
- About how often did you feel so nervous that nothing could calm you down?
- About how often did you feel hopeless?
- About how often did you feel restless or fidgety?
- How often did you feel so restless that you could not sit still?
- About how often did you feel depressed?

- About how often did you feel so depressed that nothing could cheer you up?

  <1> None of the time
  <2> Little of the time
  <3> Some of the time
  <4> Most of the time
  <5> All of the time

### E.5 Income

- I will read out a few statements about your income. Please tell me, which of the following statement is closest to your situation?
  <1> Our household income covers the needs well - we can save.
  <2> Our household income covers the needs alright, without much difficulty.
  <3> Our household income does not cover the needs, there are difficulties.
  <4> Our household income does not cover the needs, there are great difficulties.

- *(second measure will be converted for the analysis so small values refer to low income and high values to high income)

### E.6 Conjoint Experiment

### E.7 Personally Harmed

- How badly were you personally harmed by the 2015 floods?
  - <0> Not at all
  - <1> Just mildly
  - <2> Somewhat badly
  - <3> Very badly
  - <4> Extremely badly
  - <98> Don't Remember

- How badly were you economically harmed by the 2015 floods?
  - <0> Not at all
  - <1> Just mildly
  - <2> Somewhat badly
  - <3> Very badly
  - <4> Extremely badly
  - <98> Don't Remember

### E.8 Mechanism: Help

- After the 2015 floods, did you receive help?
  <0> No
  <1> Yes
  <98> Don't Remember

- If =1, From whom did you receive help?
  - <0> Nobody
  - <1> Your Traditional Authority

- <2> Your village head
- <3> Your religious leader
- <4> Your member of parliament
- <5> Your local council member
- <6> District Commissioner
- <7> NGO, International Organization
- <98> Don't Remember

*multiple answers possible

- How satisfied were you with the help you received?
  - <1> Very Satisfied
  - <2> Somewhat Satisfied
  - <3> Somewhat Dissatisfied
  - <4> Very Dissatisfied
  - <98> Don't Know/Refuse

### E.9 Expectation

- Was the flood 2015 an unexpected event?
  - <1> Entirely Expected
  - <2> Somewhat expected, but not at this magnetite
  - <3> Entirely unexpected
  - <98> Don't Remember

### E.10 Other Natural Disaster

- Between 2015 and now, was there any other adverse event such as the 2015 floods?
  - <0> No
  - <1> Yes
  - <98> Don't Remember
  - If yes, please specify:

## F Summary Statistics

Table 1: Summary Statistics Conjoint Experiment

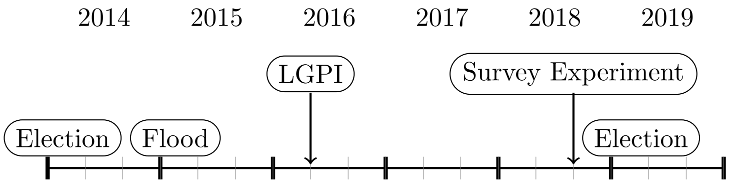
| Variable | N | Mean | Std. Dev. | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|
| Effort Preparedness | 9660 | | | | | | |
| ... Low Preparedness | 4738 | 49% | | | | | |
| ... Preparedness Coordination | 4922 | 51% | | | | | |
| Effort Relief | 9660 | | | | | | |
| ... Low Effort | 4808 | 49.8% | | | | | |
| ... Relief Coordination | 4852 | 50.2% | | | | | |
| Effective Preparedness | 9660 | | | | | | |
| ... Low Quality | 4919 | 50.9% | | | | | |
| ... Preparedness Effective | 4741 | 49.1% | | | | | |
| Effective relief | 9660 | | | | | | |
| ... did not donate | 4821 | 49.9% | | | | | |
| ... Relief Effective | 4839 | 50.1% | | | | | |
| Visit | 9660 | | | | | | |
| ... did not visit | 4784 | 49.5% | | | | | |
| ... Relief Visits | 4876 | 50.5% | | | | | |
| Honesty | 9660 | | | | | | |
| ... No Corruption | 3226 | 33.4% | | | | | |
| ... Corruption | 3204 | 33.2% | | | | | |
| ... Vote Buying | 3230 | 33.4% | | | | | |
| Ask | 9660 | | | | | | |
| ... did not ask for help | 4835 | 50.1% | | | | | |
| ... Relief Ask | 4825 | 49.9% | | | | | |
| Chosen Candidate | 9660 | 1.506 | 0.5 | 1 | 1 | 2 | 2 |
| contest | 9660 | 3.5 | 1.708 | 1 | 2 | 5 | 6 |
| candidate | 9660 | 1.5 | 0.5 | 1 | 1 | 2 | 2 |
| Choice | 9660 | 0.5 | 0.5 | 0 | 0 | 1 | 1 |

Table 2: Summary Statistics (respondent covariates)

| Variable | N | Mean | Std. Dev. | Min | Pctl. 25 | Pctl. 75 | Max |
|---|---|---|---|---|---|---|---|
| CaseID | 805 | 80431290 | 143067 | 80205300 | 80299177 | 80553498 | 80705614 |
| disaster_prime | 805 | | | | | | |
| ... control | 398 | 49% | | | | | |
| ... treatment | 407 | 51% | | | | | |
| education | 805 | 3.2 | 1.4 | 1 | 3 | 4 | 7 |
| farmer | 805 | 0.95 | 0.21 | 0 | 1 | 1 | 1 |
| manipulation | 805 | 4.2 | 1.3 | 1 | 4 | 5 | 5 |
| income | 804 | 3.4 | 0.83 | 1 | 3 | 4 | 4 |
| age | 805 | 37 | 15 | 18 | 25 | 45 | 96 |
| gender | 804 | 0.5 | 0.5 | 0 | 0 | 1 | 1 |
| income2 | 805 | 1.4 | 0.67 | 1 | 1 | 2 | 4 |
| worried | 798 | 2.7 | 0.59 | 1 | 3 | 3 | 3 |
| life2015 | 805 | 1.9 | 0.33 | 1 | 2 | 2 | 2 |
| incumbent_votingMP | 797 | 2.1 | 1.3 | 1 | 1 | 3 | 4 |
| incumbent_votingVC | 792 | 2.1 | 1.2 | 1 | 1 | 3 | 4 |
| interested_politics | 805 | 2.7 | 1.1 | 1 | 2 | 4 | 4 |
| trust_MP | 799 | 2.4 | 1.3 | 1 | 1 | 4 | 4 |
| flood_econ | 804 | 3.7 | 1.3 | 1 | 4 | 4 | 5 |
| flood_psych | 805 | 4 | 0.88 | 1 | 4 | 5 | 5 |
| personal_help | 805 | 1.2 | 0.41 | 1 | 1 | 1 | 2 |
| satisfied_personal_help | 805 | | | | | | |
| ... . | 636 | 79% | | | | | |
| ... 1 | 61 | 8% | | | | | |
| ... 2 | 64 | 8% | | | | | |
| ... 3 | 29 | 4% | | | | | |
| ... 4 | 15 | 2% | | | | | |
| disaster_post2015 | 805 | 1.4 | 0.48 | 1 | 1 | 2 | 2 |
| personal_help_id3 | 805 | | | | | | |
| ... . | 793 | 99% | | | | | |
| ... 10 | 5 | 1% | | | | | |
| ... 11 | 1 | 0% | | | | | |
| ... 9 | 6 | 1% | | | | | |
| personal_help_id4 | 805 | | | | | | |
| ... . | 803 | 100% | | | | | |
| ... 10 | 2 | 0% | | | | | |
| community_help_id3 | 805 | | | | | | |
| ... . | 788 | 98% | | | | | |
| ... 7 | 5 | 1% | | | | | |
| ... 8 | 11 | 1% | | | | | |
| ... 9 | 1 | 0% | | | | | |
| community_help | 797 | 1.6 | 0.48 | 1 | 1 | 2 | 2 |
| distance_flood | 805 | 5156 | 6904 | 0 | 292 | 11071 | 19983 |
| elevation | 805 | 121 | 66 | 47 | 59 | 191 | 234 |
| hours | 805 | 0.37 | 0.17 | 0.17 | 0.29 | 0.41 | 2.6 |
| poverty | 805 | 0.88 | 0.33 | 0 | 1 | 1 | 1 |

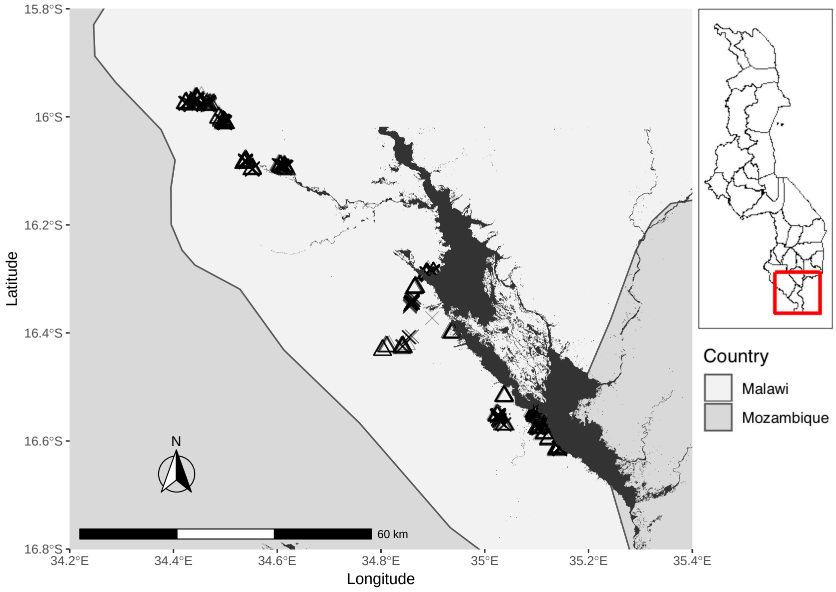
# G Sampling

Figure 7: Timing of Elections, Flood and Data Collections.




I draw on the same villages that were part of the Local Governance and Performance Index (LGPI) in 2016 (Lust et al. 2016). The LGPI survey collected public opinion data on public service provision in Malawi and provides extensive background data on each village. The respondents from each data collection are not the same, but they were selected randomly from within the same villages. The LGPI sample was stratified on region (North, Central, South), the presence of matrilineal and patrilineal ethnic groups, and the 'urban'/rural divide. Because patrilineal groups are rare in Malawi and we wanted to maximize variation in matrilineal and patrilineal heritage, we oversampled Primary Sampling Units (PSUs) from the patrilineal stratum. We sampled 22 PSUs, namely 'Traditional Authorities' (TAs). These 22 sampled TAs are in 15 of Malawi's 28 districts. Within each TA (i.e., PSU), we selected randomly four enumeration areas (EAs) as Secondary Sampling Units (SSUs). EAs are comparable to census tracts. Both PSUs and SSUs were selected without replacement according to the principle of Probability of Selection Proportional to Measure of Size (PPMS). Within each EA, four villages were sampled based on known geographical points provided on the maps of the EAs produced for Malawi's latest population census. Once in the village, enumerators followed a random walk pattern to select households. After they entered the household, the interviewer collected the necessary data about composition of the household. Both the contact questionnaire and the main questionnaire we programmed on digital tablets, including the selection of the final respondent in the household through a digital version of the "Kish grid". Before returning to the villages, (1) I superimposed all exact geo-locations of previous respondent onto satellite imagery (Google Earth) and (2) identified the center of the village cluster. Once the center of the village was identified, I saved all geo-locations are made them available to enumerators.

Figure 8: Map of Southern Malawi Depicting the Extent of the Flooded Area in 2015 (in black) and Survey Locations in 2016 (△) and 2018 (×)



# H Conjoint Experiment

## H.1 Estimand

The AMCE measures the marginal effect of a given attribute of a conjoint profile on respondents' support for the overall profile relative to a baseline, averaged over the joint distribution of other attributes (Hainmueller, Hopkins, and Yamamoto 2014). The baseline of a given attribute is always 0. I use a uniform distribution when randomizing over levels of factors. Because attributes are randomly assigned, the given attribute level and attribute baseline will have, in expectation, the same distribution for all the other attributes. The AMCE combines two part of individual preferences: their direction (whether or not an individual prefers $A$ to $\neg A$) and their intensity (how much they prefer $A$ to $\neg A$). As shown by Abramson, Kocak, and Magazinnik (2022), a positive AMCE of a given attribute $A$ does necessarily mean that a majority of respondents prefer $A$ to $\neg A$ because a minority could hold this preference, but this minority could hold this preference more intensely. Instead, the AMCE can be interpreted as the average marginal causal effect of a given attribute on a candidate's expected vote share, given a particular randomization distribution (Bansak et al. 2022). Put differently, the AMCE can be interpreted as the causal effect of a candidate attribute (providing relief funds vs. not providing relief funds etc.) on vote shares in an election matching the specifications of the conjoint. I employ this interpretation in the subsequent analyses because Malawi has a plurality systems and MPs often win with less than 50% of the vote. Therefore, marginal effects are informative.

## H.2 Estimation

I estimate the AMCE using an OLS regression with heteroskedasticity-robust standard errors clustered at the individual:

$$Y_i = \sum_{j \in Z} \beta_j Z_i^j + \varepsilon_i \tag{1}$$

where $Y$ is the chosen candidate policy profile for choice $i$, $j$ indexes the factor level and $Z$ is a set of indicators corresponding to the attributes.

### H.3 Conjoint Introduction

*'This section attempts to understand what kind of candidate you would support in an election. We will show you profiles of hypothetical local candidates running for MP and how they handled a recent flood. Imagine that you live in a different district similar to yours in this region that was affected by a flood and that you were voting for candidates in elections. Here are the two candidates who are running against each other. You should tell us whom do you prefer. They are both men, have the same age (around 50), and come from the same tribe. However, there are important differences between the two:"*

### H.4 Conjoint Example

Table 3: Conjoint Experiment: Exemplifying Profiles of Candidates, as shown to Respondents

| Factor ($Z$) | MP 1 | MP 2 |
|---|---|---|
| **Effort** | | |
| Preparedness | (0) *Did not* put a lot of work into disaster preparedness plan | (1) *Did* put a lot of work into disaster preparedness plan |
| Relief | (0) *Did not attend* meetings to co-ordinate disaster relief | (1) *Did attend* meetings to co-ordinate disaster relief |
| **Effective** | | |
| Preparedness | (0) Preparedness plan was of *low quality* and did not limit the damages from the flood | (1) Preparedness plan was of *high quality* and did limit the damages from the flood |
| Relief | (0) *Did not donate* funds to the village | (1) *Did donate* funds to the village |
| **Other** | | |
| Ask | (0) *Did not ask* for help from funders | (1) *Did ask* for help from funders |
| Visit | (0) *Did not visit* the disaster site | (1) Did visit the disaster site, talked to victims and declared his solidarity. |
| Corruption | (0) No record of corruption | (1) is convicted for embezzling humanitarian aid for personal use<br>(2) is convicted of corruption for handing out cash to buy votes |
| **Choice** | | |

### H.5 Plausibility of Conjoint Profile Combinations

Are all combinations in the conjoint experiment plausible? In particular, is the combination of 'low effort (relief or preparedness) - high effectiveness (relief or preparedness)' plausible. A short narrative may illustrate the issue. Consider a candidate politician preparing for and reacting to a disaster. Assume that highly competent politicians have better policy ideas, while less competent politicians have worse policy ideas. However, candidates of both low and high competence can exert varying levels of effort in their work. For instance, a politician could invest a high or low amount of effort into a preparedness policy. Competence, on the other hand, links the amount of effort a politician invests with the final outcome (the successful implementation of the plan). Abstractly, one might think of competence as the marginal productivity of an input of work, that is, the change in outcome produced by each unit of work input. For example, less competent candidates can invest many working hours into a preparedness plan, but the quality of the policy will be poor and ineffective. High-quality candidates, on the other hand, are intelligent and can produce reasonably good results (output) even if they invest little effort. Additionally, the effectiveness of a policy might also depend on a certain amount of chance (lucky or unlucky circumstances influencing implementation). In summary, respondents may have interpreted the combination of low efforts and effective outcomes as resulting from either fortunate circumstances and/or high competence. Additionally, I tested the conjoint at the Institute for Public Opinion Research, and respondents did not note anything about this type of profile combination.

# I Main Results

Table 4: Main Results

| | Model 1 |
|---|---|
| (Intercept) | 0.31*** |
| | (0.01) |
| Preparedness Coordination | 0.05*** |
| | (0.01) |
| Relief Coordination | 0.09*** |
| | (0.01) |
| Preparedness Effective | 0.11*** |
| | (0.01) |
| Relief Effective | 0.12*** |
| | (0.01) |
| Relief Ask | 0.12*** |
| | (0.01) |
| Visits | 0.16*** |
| | (0.01) |
| Corruption | −0.24*** |
| | (0.01) |
| Vote Buying | −0.17*** |
| | (0.01) |
| Num.Obs. | 9660 |
| R2 | 0.117 |
| R2 Adj. | 0.116 |
| Std.Errors | by: CaseID |

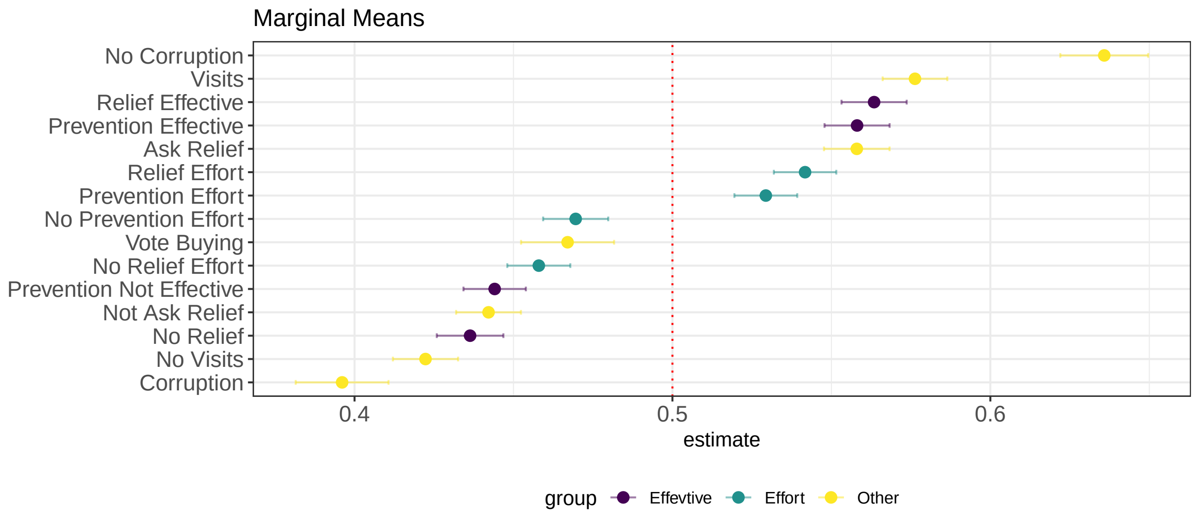
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Notes**: OLS estimates with robust standard errors within parentheses.

### I.1 Marginal Means

Following Leeper, Hobolt, and Tilley (2020), I also estimate the marginal means of each attribute level. A marginal mean is a factor-level mean support for the candidate averaged over all other factor levels (Leeper, Hobolt, and Tilley 2020).

Figure 9: Marginal Means




*Notes: Beta coefficients from OLS regression with robust standard errors in parentheses. Standard errors are clustered at the individual level. Horizontal lines indicate 95% confidence intervals. The baseline is always the low level of the given attribute.*

### I.2 Linear Hypothesis

Table 5: Main Results, Linear Hypothesis 1

| | Model 1 |
|---|---|
| (Intercept) | 0.31*** |
| | (0.01) |
| Preparedness Coordination | 0.05*** |
| | (0.01) |
| Relief Coordination | 0.09*** |
| | (0.01) |
| Preparedness Effective | 0.11*** |
| | (0.01) |
| Relief Effective | 0.12*** |
| | (0.01) |
| Relief Ask | 0.12*** |
| | (0.01) |
| Visits | 0.16*** |
| | (0.01) |
| Corruption | −0.24*** |
| | (0.01) |
| Vote Buying | −0.17*** |
| | (0.01) |
| Effort prevention - Effort relief = 0 | −0.03** |
| | (0.01) |
| Num.Obs. | 9660 |
| R2 | 0.117 |
| R2 Adj. | 0.116 |
| Std.Errors | HC2 |

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Note**: OLS estimates with robust standard errors within parentheses.

Table 6: Main Results, Linear Hypothesis 2

| | Model 1 |
|---|---|
| (Intercept) | 0.31*** |
| | (0.01) |
| Preparedness Coordination | 0.05*** |
| | (0.01) |
| Relief Coordination | 0.09*** |
| | (0.01) |
| Preparedness Effective | 0.11*** |
| | (0.01) |
| Relief Effective | 0.12*** |
| | (0.01) |
| Relief Ask | 0.12*** |
| | (0.01) |
| Relief Visits | 0.16*** |
| | (0.01) |
| Corruption | −0.24*** |
| | (0.01) |
| Vote Buying | −0.17*** |
| | (0.01) |
| Preparedness Effective - Relief Effective = 0 | −0.01 |
| | (0.01) |
| Num.Obs. | 9660 |
| R2 | 0.117 |
| R2 Adj. | 0.116 |
| Std.Errors | HC2 |

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Notes**: OLS estimates with robust standard errors within parentheses.

Table 7: Main Results with Interactions

| | Model with interactions |
|---|---|
| Preparedness Effort | 0.05* |
| | (0.02) |
| Relief Effort | 0.09*** |
| | (0.02) |
| Preparedness Effective | 0.11*** |
| | (0.02) |
| Relief Effective | 0.10*** |
| | (0.02) |
| Corruption | −0.24*** |
| | (0.02) |
| Vote Buying | −0.18*** |
| | (0.02) |
| Preparedness Effective × Corruption | −0.01 |
| | (0.02) |
| Preparedness Effective × Vote Buying | 0.01 |
| | (0.02) |
| Relief Coordination × Relief Effective | 0.01 |
| | (0.02) |
| Preparedness Effective × Relief Effective | −0.01 |
| | (0.02) |
| Preparedness Effort × Relief Coordination | −0.01 |
| | (0.02) |
| Preparedness Effort × Preparedness Effective | 0.00 |
| | (0.02) |
| Preparedness Effort × Corruption | 0.01 |
| | (0.02) |
| Preparedness Effort × Vote Buying | 0.00 |
| | (0.02) |
| Relief Effective × Corruption | 0.02 |
| | (0.02) |
| Relief Effective × Vote Buying | 0.03 |
| | (0.02) |
| Num.Obs. | 9660 |
| R2 | 0.078 |
| R2 Adj. | 0.076 |
| Std.Errors | by: CaseID |

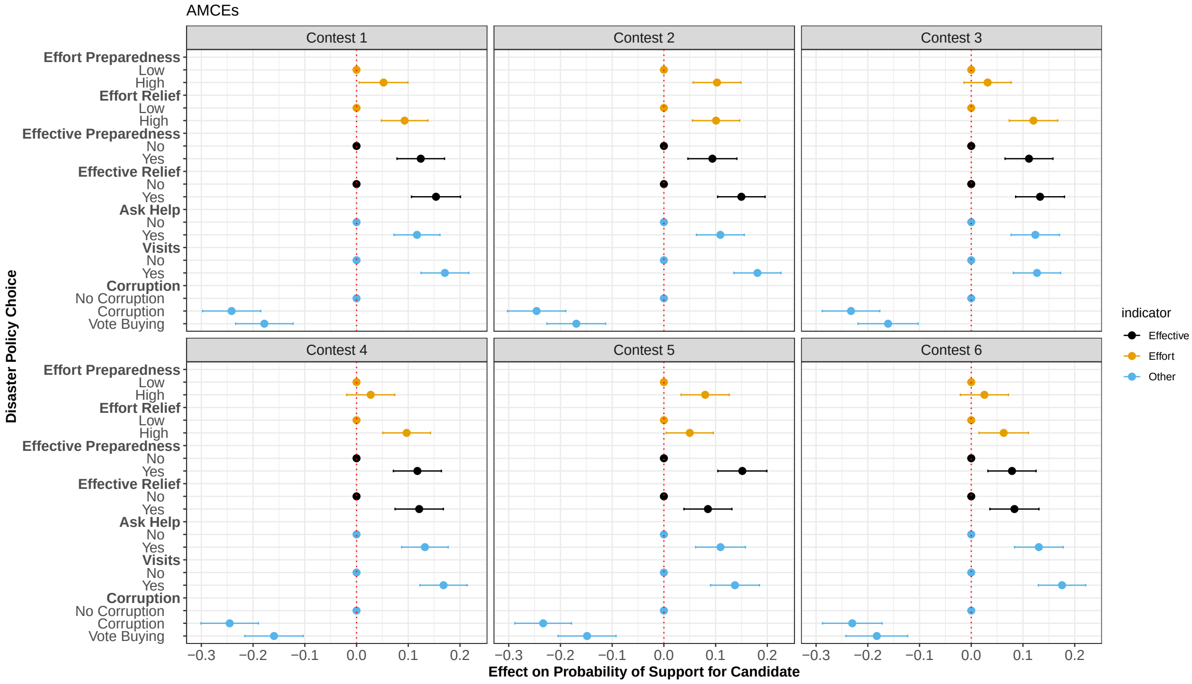
+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Notes**: OLS estimates with robust standard errors within parentheses.

## I.3 Main Results with Interactions

## I.4 Main Effects, Heterogeneity of AMCE by Number of Contest

Figure 10: Heterogeneity of AMCE by Number of Contest



# J Additional Results

- $H_{3a}$: Voters who experienced economic losses will be more likely to reward candidates who delivered relief benefits and provided cash to buy votes.

- $H_{3b}$: Voters primed for economic hardship will be more likely to reward candidates who delivered relief benefits and provided cash to buy votes.

Note: Only $H_{3b}$ was pre-registered (see Appendix C). Additionally, I pre-registered an explorative analysis: "I will investigate if the distance from each respondent to the actual flood in 2015 influences how important different candidate characteristics are for voters. I use the geolocations (longitude,latitude) of respondents with respect to the 2015 flood and combine them with data collected during the survey. My working hypotheses are similar to the ones [above], namely that respondents who live closer to the 2015 flood, i.e. had more exposure to the floods, are more likely to prefer candidates that deliver material benefits and are more likely to accept candidates the engage in vote-buying. The indicator for flood exposure is a function of the euclidian distance from each respondent to the 2015 flood."

## J.1 Conditional AMCE's by Respondent Affectedness

Having established that respondents hold expectations about the effectiveness of prevention and relief policies, I investigated to what extent preferences are subject to change due to individuals' affectedness (Hypotheses 3a–3b). I measure exposure to the natural disaster with three different indicators: distance to the flood in 2015, self-reported economic losses due to the 2015 flood, and primed psychological and financial distress due to a natural disaster. Economic losses are defined as a binary measure taking the value of 1 if the respondents reported they were very badly harmed by the 2015 flood and 0 otherwise.[2] To measure the effect of psychological distress, I randomly assign a natural disaster prime before the conjoint experiment. The prime is intended to induce financial worries while leaving the actual economic state of the respondent unchanged. The design was developed by Mani et al. (2013). I use a hypothetical scenario about locusts destroying the harvest because it is a common problem.[3] The control group did not receive the prime.

## J.2 Distance to the flood

In order to assess the extent of a maximum flood and the distance from each respondent to the flood, I create a maximum flood polygon by merging publicly available GIS-data obtained from the Malawi Spatial Data Platform from several satellite programs: the TerraSAR-X, RADARSAT-2, and Copernicus EMS.[4]. Flooded areas by RADARSAT-2 as of 13/01/2015, flooded areas by TerraSAR-X as of 10/01/2015, and flooded areas by Copernicus EMS as of 27/01/2015. The image with the highest resolution comes from RADARSAT-2 and has a spatial resolution of 6.25 meters. However, high-resolution satellite data was only available for the Shire valley and the Zomba district. This includes the districts Nsjanje, Chikwawa, Mulanje. This is partly because the meteorological situation was complex. In particular, the rainfalls occurred over a time period of about two weeks during early January. Heavy rains hit the country two times, first on January 8 and 9 with rainfall of up to 100 mm–subsequently leading to the riverine floods of the Shire river approximately on January 10-13–and on January 12 with up to 400 mm–leading to the the flash floods–with both riverine floods around the Shire river and flash floods in larger cities such as Blantyre (Kruczkiewicz et al. 2016). Since remote sensing

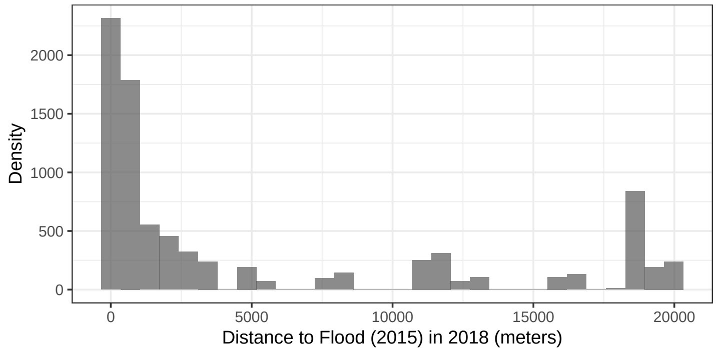
[2]See the exact wording and distribution in Figure 14. In the pre-analysis plan, I specified to also test heterogeneous effects on ACMEs depending on the distance to the flood.

[3]The prime included an open-ended question: *"Treatment: Imagine you are a farmer and that locusts destroy your entire crop and the whole harvest is lost. How do you deal with this situation? Does it cause you serious financial hardship? Does it require you to make sacrifices? If so, what kind of sacrifices?"* For the details see Appendix J.4.

[4]MASDAP, see http://www.masdap.mw/

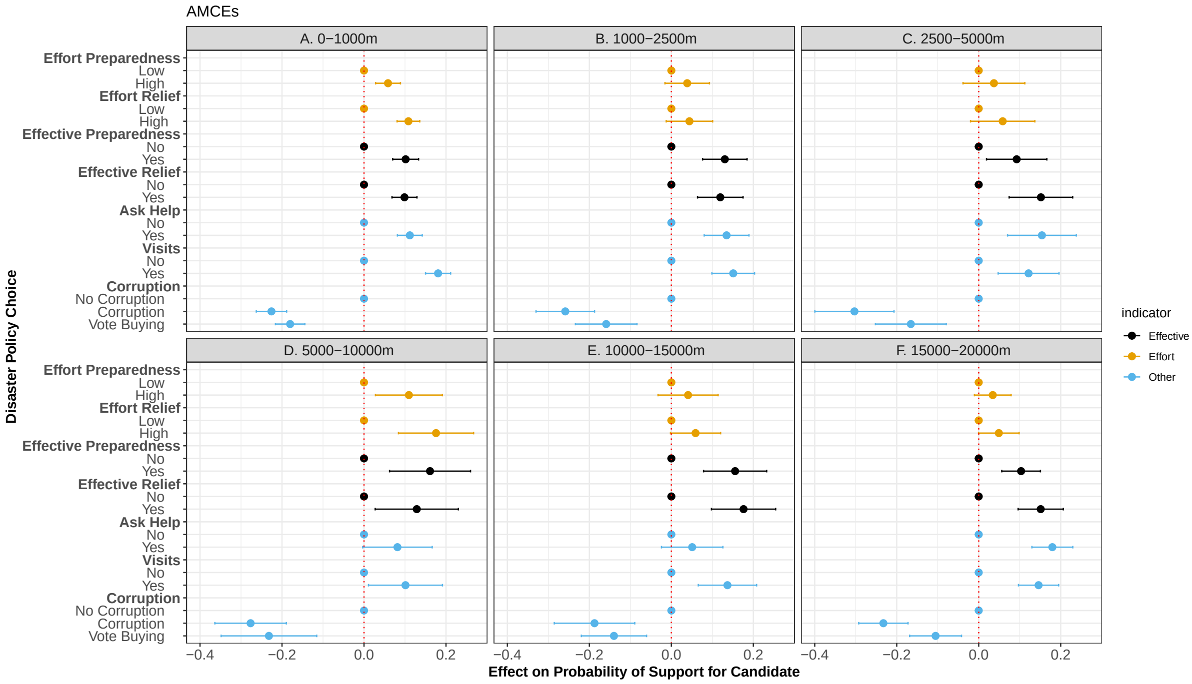
satellites can only detect larger water areas as produced by riverine floods, I am not able to access the extent of the flash floods.

Figure 11: Distance to Flood (2015) in 2018.



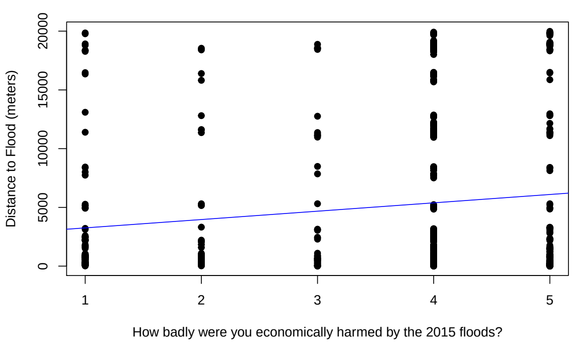

For the analysis, I subsetted the data to include respondents who reported living in the same community as in 2015, which resulted in a loss of roughly 10 percent of the sample. As we can see in the plot below, most respondents reside in households within approximately a 5-kilometer distance from the flooded areas, peaking at roughly 1 km. However, some households are further away, with notable peaks between 10 km and 15 km, as well as between 15 km and 20 km. Based on this distribution, I divided the data into six categories: 0-1000 m, 1000-2500 m, 2500-5000 m, 5000-10000 m, 10000-15000 m, and 15000-20000 m. I then conducted the main analysis on these sub-samples, according to geographic distance. The results, reported in the figure below, show the Average Marginal Component Effects (AMCEs) along with cluster-robust 95% confidence intervals for each distance category. As observed, respondents living in areas close to the flood zone (0-1000 m) display the same patterns seen in the main analysis. Specifically, respondents reward relief efforts over preparedness efforts, but they value effective preparedness similarly to effective relief. Respondents living further from the flooded areas do value candidates who implement effective preparedness policies and provide effective relief. However, these respondents demonstrate less support for both preparedness and relief efforts; the point estimates are indistinguishable from zero in almost all sub-samples, except for the 5000-10000 m category. This could suggest that respondents less exposed to the flood do not inherently value efforts, possibly due to less experience with the benefits such efforts can offer. Conversely, respondents who were more exposed to the flood support candidates who invested in preparedness and relief efforts, possibly because they have had more exposure to those efforts and are more likely to link them to effective outcomes. All subgroups, however, similarly support candidates who provide effective relief and those who implement effective preparedness policies. The point estimates (visits, corruption, etc.) are also fairly similar across distance groups. Readers should note that all results are purely descriptive and do not make any causal claims.

Figure 12: Heterogeneity of AMCE by Distance to Flood in 2015




However, there is one caveat to note. I pre-registered an exploratory analysis of geographic variation in the pre-analysis plan. However, I did not include this analysis in the previous version of the manuscript because the pre-specified distance measure proved to be a poor predictor of self-reported economic losses, which is the main concept of interest. The scatter plot below illustrates the distance of respondents to the flooded area in 2015 in meters on the X-axis and self-reported economic losses in the survey on a scale of 1-5, with higher values indicating greater losses. The plot indicates that respondents who lived closer to the flooded areas were less likely to report having endured economic hardship. There could be several reasons for this correlation. Since the majority of respondents are farmers, the economic losses they reported are likely related to their agricultural fields and/or housing. However, the distance measure would only be relevant if the fields are located close to the houses, which may not always be the case. Additionally, the self-reported measure of economic losses could be misleading. At this point, it is unclear which of the two is a more accurate measure of exposure to the natural disaster. Therefore, I have included a heterogeneity analysis for both measures.

Figure 13: Scatterplot Economic Distress (X) and Distance to Flood (Y)?



### J.3 Self-reported economic losses

Next, I explore the effects of self-reported economic losses due to the flood. The figure below displays the distribution of this variable. We can see that the majority of respondents report having endured major economic challenges due to the flood in 2015, while only a very small minority reported no losses. For the analysis, I create a binary measure that assigns a value of 0 if respondents report having suffered 'Somewhat', 'Just mildly', or 'Not at all', and a value of 1 if respondents report being affected 'Very badly' or 'Extremely badly'. I estimate the conditional AMCE with respect to the moderating variables $T$ and economic losses. For this purpose, I use OLS with interactions of attributes and moderators to estimate equation 2:

$$Y_{im} = \sum_{j \in Z} \beta_j Z_i^j + \sum_{j \in Z} \theta_j (Z_i^j * T_i) + \alpha T_i + \sum X_i + \varepsilon_i \tag{2}$$

The conditional ACMEs ($\theta_j$) of self-reported economic losses must be interpreted with care because economic losses were not randomly assigned. For the effect of economic losses, I also control for a set of covariates $X_i$ that could influence both economic losses and the reaction to the attributes in the conjoint: poverty levels, education, gender, interest in politics, geographic distance to the flood in 2015, help received after the last disaster, and trust in MPs.[5] Second, I also report the conditional marginal means (Leeper, Hobolt, and Tilley 2020).

Figure 14: Flood exposure

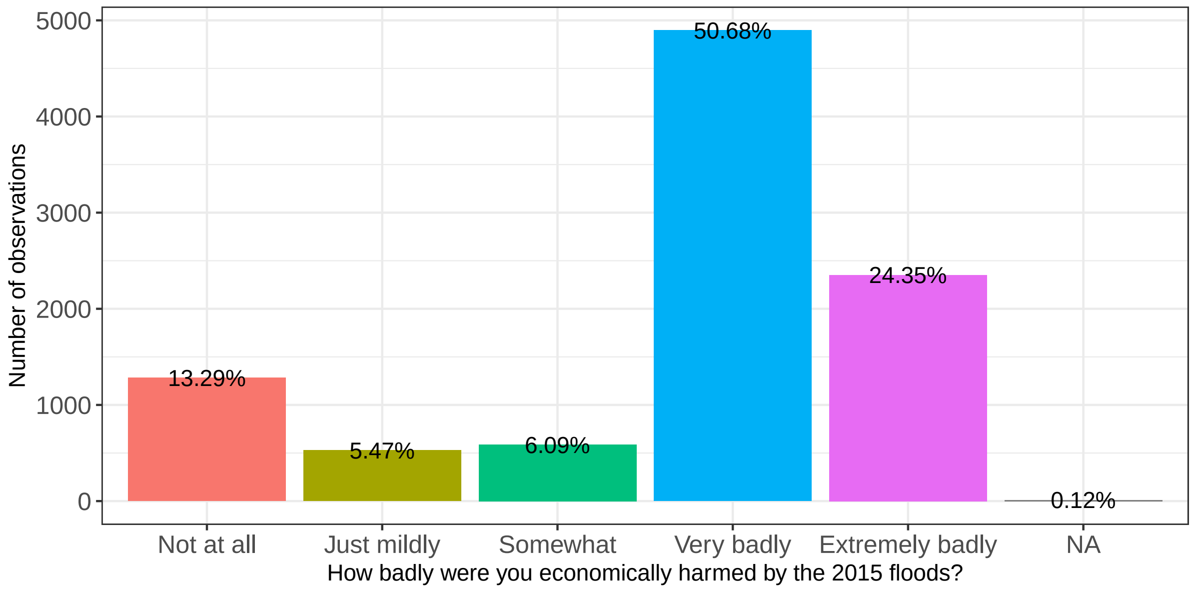
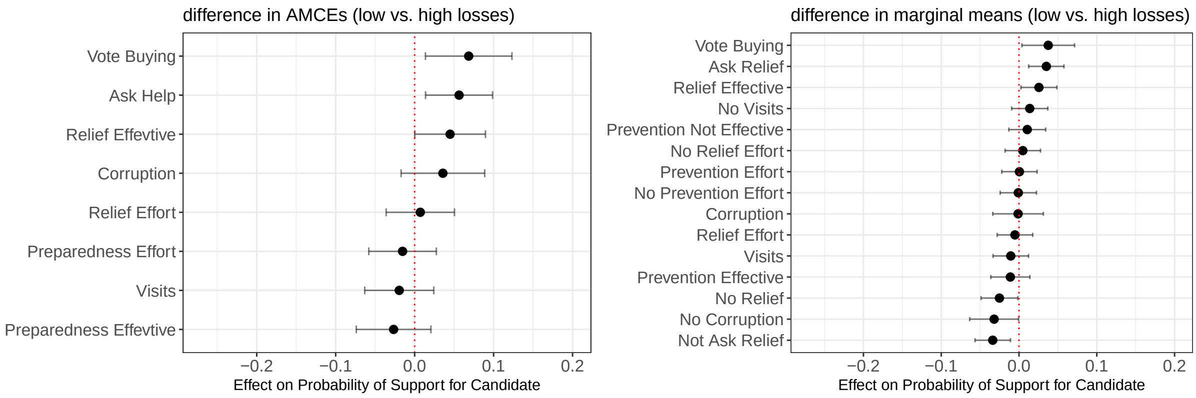



Figure 15 shows the conditional AMCEs, along with 95% confidence intervals. The left panel displays the difference in AMCEs for respondents with low vs. high economic losses, and the right panel displays the difference in marginal means for respondents with low vs. high economic losses. Examining the differences in AMCEs, we observe that, on average, changing economic losses from control (not at all, just mildly, somewhat) to treatment (very badly, extremely badly) increases the probability of supporting a candidate who delivers disaster relief by an average of 0.04 percentage points. The probability of supporting a candidate who used vote-buying strategies also moves in the predicted direction: voters are more likely to reward candidates who engaged in vote-buying (0.06) if they have experienced recent economic losses. However, it is important to note that the coefficient on the vote-buying attribute remains negative. Voters are also more likely to support candidates who sought help from external actors. All

[5] See Appendix E for the description of the survey measurements.

three point estimates are statistically significant at conventional levels (0.05). It is also worth noting that the point estimates for preparedness efforts and effective preparedness are lower for individuals who have experienced high losses, although the difference is not statistically significant. The results are robust to the inclusion of several pre-treatment control variables, such as poverty, political engagement, and education levels.[6] The results remain substantively unchanged if we look at the difference in marginal means (right panel).

Figure 15: Difference in AMCEs and Marginal Means with 95 percent confidence intervals and clustered standard errors; by Economic Losses: control (not at all, just mildly, somewhat) to treatment (very badly, extremely badly).



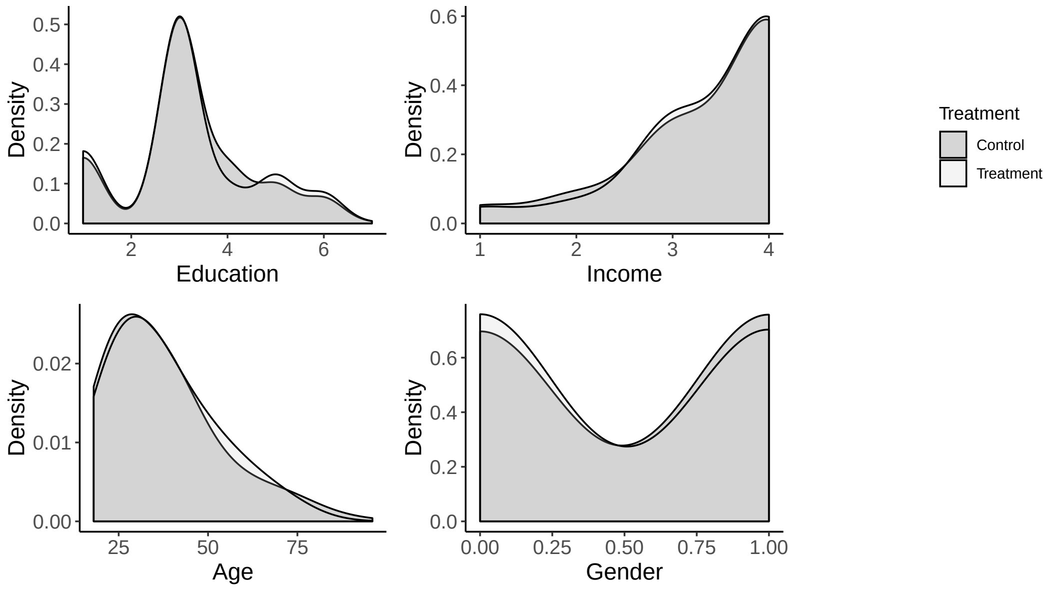

[6]See regression Table 9 with controls.

### J.4 Psychological distress, disaster prime

Next, I test the effect of psychological distress on voter preferences ($H_{3b}$). I included a randomly assigned prime before the conjoint experiment to influence psychological stress: **Treatment: Imagine you are a farmer and that locusts destroy your entire crop and the whole harvest is lost. How do you deal with this situation? Does it cause you serious financial hardship? Does it require you to make sacrifices? If so, what kind of sacrifices? Control: [empty]** I decided to not include an economic scenario that is directly linked to the flood because such a treatment could induce bias: it could influence the perception of some attributes in the conjoint experiment that are also directly linked to the disaster. Respondents are given some time to contemplate about how they might deal with these problems. Specifically, the treatment induces thoughts about financial worry and potential sources of help during such a crisis. This scenario shares some common features with flood disasters. Harvest failures are a big economic concern for many people in the sample villages in the Shire valley.[7] Farming is also common in the villages included in the sample. Using survey data from the same villages (Lust et al. 2016), I find that over 96% of respondents noted that they farm land and 85% stated that farming is their main sector of work.

Figure 16 shows the balance of covariates for respondents who randomly received the prime (treatment) and those who did not (control).

Figure 16: Balance Tests : Respondent Characteristics (Distress Prime Experiment)




### J.5 Manipulation Check: Economic Distress Prime

Table 8 shows the manipulation test for the disaster prime. We can see that the prime was successful and only manipulated financial worries.

Looking at the prime's effect in Figure 17, preferences are remarkably stable across the treatment and control comparisons and do not show the predicted effects. Therefore, I cannot reject the null hypothesis of no effect of psychological distress on demand for relief benefits. If anything, respondents primed for economic distress became more dismissive of candidates engaging in vote-buying. The point estimates are negative and statistically significant at the 0.1 level. The other point estimates remained unchanged. One possible explanation is that the prime was too weak to induce financial distress. However, as we can see in Table 8, the prime increased financial worries in the treatment group. Alternatively, the prime might only

[7] See: https://mwnation.com/2016-locusts-worsened-food-shortage-in-shire-valley/

Table 8: Manipulation Check

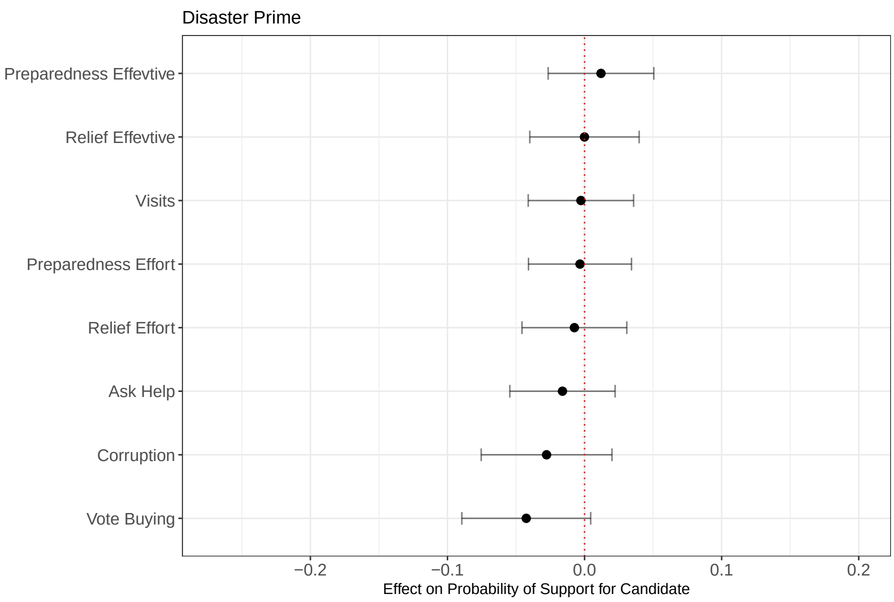
| Outcome | Effects Size |
|---|---|
| Financial Worry | $0.18^{*}$ |
| | (0.09) |
| MP Responsible Relief | 0.06 |
| | (0.05) |
| MP Responsible Preparedness | 0.04 |
| | (0.05) |
| Flood Worry | $-0.00$ |
| | (0.04) |
| Hopeless | 0.10 |
| | (0.10) |
| Num. obs. | 806 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\cdot}p < 0.1$

**Notes**: OLS estimates with robust standard errors within parentheses.

have induced the desired effects for a subset of participants. I explored this possibility and evaluated how the prime affected participants who experienced high or low losses during a natural disaster. Taken together, I find tentative evidence that economic losses due to natural disasters might induce demand for vote-buying and material benefits (Gallego 2018; Cavalcanti 2018), but the average marginal effect of vote-buying is still negative in the group with high losses. However, the economic effect persisted for two years after the disaster, likely because respondents did not receive sufficient help in the immediate aftermath (see Figure 14). Thus, the results lend some support to findings that disaster events can alter political preferences (Fair et al. 2017), can have long-lasting political consequences (Bechtel and Hainmueller 2011), and point to the importance of insurance against disaster-related economic losses (Clarke and Dercon 2016).

Figure 17: Difference in AMCEs of Attributes on Candidate Support, by disaster prime




*Notes: Beta coefficients from OLS regression with standard errors in parentheses. Standard errors are clustered at the individual. Vertical lines indicate 95% confidence intervals.*

Table 9: Effect of Economic Losses, Full Models, with Controls

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| Prevention Effort x Economic Losses | $-0.02$ | $-0.02$ | $-0.02$ | $-0.02$ | $-0.02$ |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Relief Effort x Economic Losses | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Relief Ask x Economic Losses | $0.06^{***}$ | $0.06^{***}$ | $0.06^{***}$ | $0.05^{**}$ | $0.06^{**}$ |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Prevention Effective x Economic Losses | $-0.03$ | $-0.03$ | $-0.03$ | $-0.03$ | $-0.03$ |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Relief Effective x Economic Losses | $0.04^{*}$ | $0.04^{*}$ | $0.04^{*}$ | $0.04^{*}$ | $0.04^{*}$ |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Visits x Economic Losses | $-0.02$ | $-0.02$ | $-0.02$ | $-0.02$ | $-0.02$ |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| Corruption x Economic Losses | 0.04 | 0.04 | 0.04 | 0.03 | 0.04 |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| Vote Buying x Economic Losses | $0.07^{**}$ | $0.07^{**}$ | $0.07^{**}$ | $0.06^{**}$ | $0.06^{**}$ |
| | (0.03) | (0.03) | (0.03) | (0.03) | (0.03) |
| Poverty | | 0.00 | 0.00 | 0.00 | 0.01 |
| | | (0.01) | (0.01) | (0.01) | (0.01) |
| Education | | | | $-0.00$ | $-0.00$ |
| | | | | (0.00) | (0.00) |
| Age | | | | $-0.00^{***}$ | $-0.00^{**}$ |
| | | | | (0.00) | (0.00) |
| Gender | | | | $-0.01$ | $-0.01$ |
| | | | | (0.00) | (0.00) |
| Interested Politics | | | | 0.00 | 0.00 |
| | | | | (0.00) | (0.00) |
| Trust MP | | | | $-0.00$ | $-0.00$ |
| | | | | (0.00) | (0.00) |
| Flood Worried | | | | | 0.00 |
| | | | | | (0.00) |
| Received Help | | | | | $-0.00$ |
| | | | | | (0.00) |
| Economic Losses x Poverty | | | | | $-0.01$ |
| | | | | | (0.02) |
| $R^2$ | 0.12 | 0.12 | 0.12 | 0.12 | 0.12 |
| Num. obs. | 9648 | 9648 | 9648 | 9564 | 9480 |
| N Clusters | 804 | 804 | 804 | 797 | 790 |

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

**Notes**: OLS estimates with robust standard errors within parentheses.

## K Voter information: disaster preparedness vs. disaster relief policies

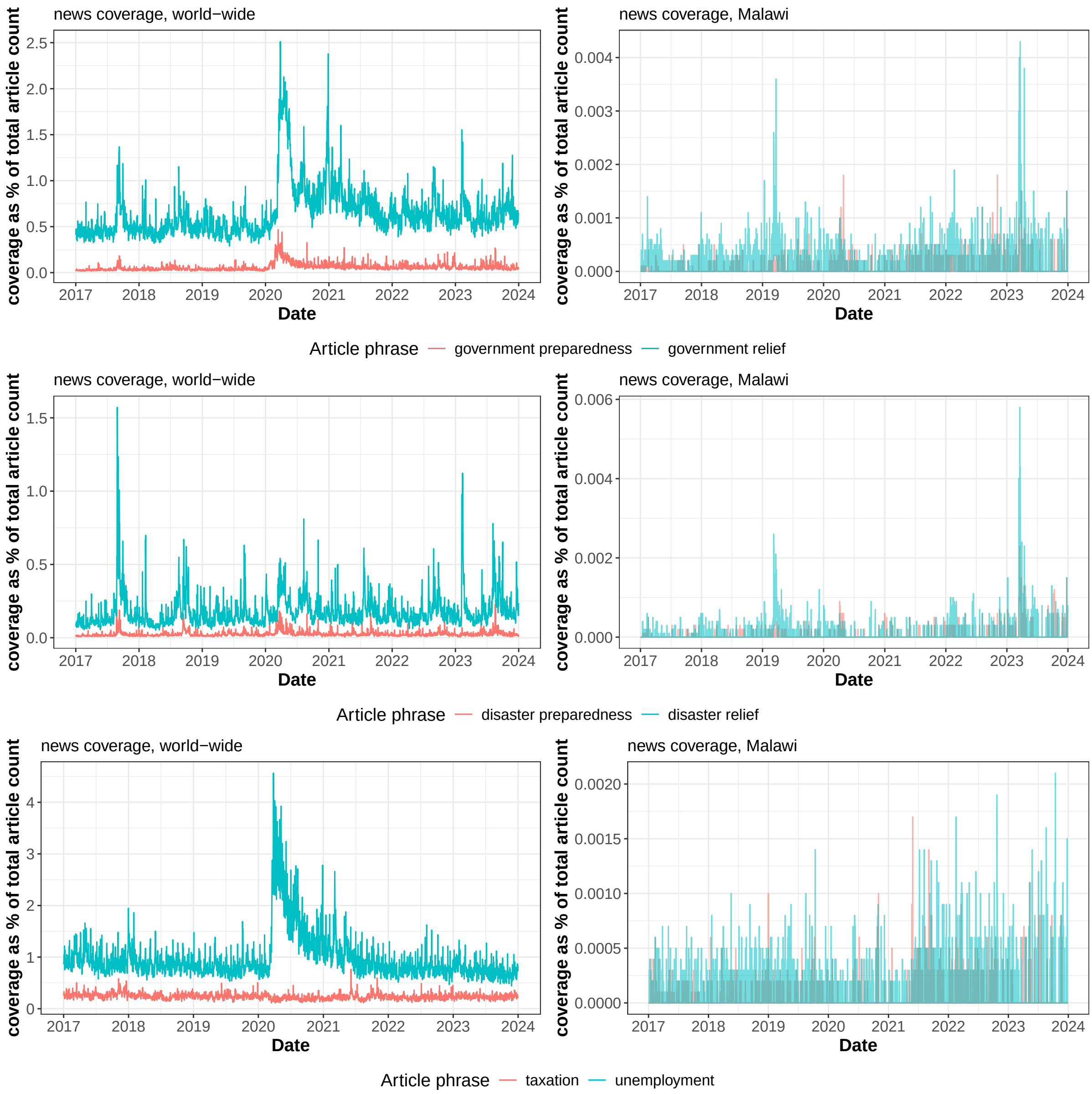
- **Examples: information about disaster policy efforts**
  - **Government media briefings**
    - **South Africa** The government proactively engages in media briefings to inform about seasonal forecasts and preparedness measures. For instance, the Ministerial Intergovernmental Committee on Disaster Management briefed the media on the Summer Seasonal Forecast, discussing disaster mitigation and seasonal preparedness measures to protect lives, property, livelihoods, and services. This briefing was part of an effort to outline the seasonal profile's implications, disaster risk readiness, and preparedness levels from various sectors, including water and sanitation, to mitigate potential flooding occurrences and other disasters. Source: https://www.gov.za/news/media-statements/media-briefings/government-briefs-media-summer-season-forecast-and-disaster
- **Examples: communicating effective preparedness**
  - **Public speeches by politicians**:
    - **Pakistan**: In a statement during the 7th Session of the Global Platform for Disaster Risk Reduction in Bali, Indonesia, Lieutenant General Akhtar Nawaz, Chairman of the National Disaster Management Authority of Pakistan, highlighted the country's progress and success in disaster preparedness and management. Source:
    - **Bangladesh** Prime Minister Sheikh Hasina today called upon the people to be cautious and aware to reduce risks of natural calamities."Now, we can know about cyclones earlier with the help of technology . . . be cautious and aware to reduce risks in any disaster," she said. Source: https://www.tbsnews.net/environment/adequate-measures-being-taken-save-people-natural-disasters-pm-249595
  - **Media coverage**
    - **Malawi** The partnership between the government of Malawi and NGOs, notably through CARE's support and USAID funding, significantly enhanced disaster preparedness in Malawi, as demonstrated during Cyclone Idai in 2019. This collaboration led to the formation of civilian protection committees in communities like Chilanga, Nsanje district, which were trained to anticipate and respond to natural disasters effectively. An essential outcome of this partnership was the construction of an evacuation center, which provided a safe haven for over 4,000 residents during the cyclone, preventing any fatalities: "So far, there have been no deaths reported due to flooding in Chilanga. And government officials here say the community's efforts to better prepare for disaster played a large role in saving people's lives. "This was a unique idea and it has helped a lot in making the lives of the displaced people better," said Emmanuel Mbenuka, a government Social Welfare Assistant based in Nsanje." Source: https://www.care.org/news-and-stories/news/disaster-preparedness-saves-lives-in-ma
    - **India** The article describes the development of Odisha's disaster management strategies in response to a series of cyclones over the past two decades. Initially, the 1999 super cyclone, which claimed over 10,000 lives and left millions homeless, underscored the state's vulnerability and the urgent need for a robust disaster preparedness framework. Highlighting the transformation, the article contrasts this tragedy with the subsequent handling of Cyclone Phailin in 2013,

Hudhud in 2014, Titli in 2018, and Fani in 2019. These later events saw significantly reduced fatalities and damages, thanks to improved early warning systems, community-level planning, and infrastructure resilience.Source: https://www.hindustantimes.com/cities/cyclone-yaas-how-odisha-s-model-of-disaster-preparedness-html

## K.1 Media Coverage: disaster preparedness vs. disaster relief

First, I analyse news coverage of disaster policies. I rely on the Global Database of Events, Language, and Tone (GDELT) (Leetaru and Schrodt 2013) and its DOC 2.0 API, offering access to news articles in 65 languages globally. The data are based on news reports from a variety of international news. The API facilitates searches in multiple languages using English keywords through GDELT's Translingual platform, which translates its entire monitored content in these languages. This accounts for 98.4% of its daily volume from non-English sources.

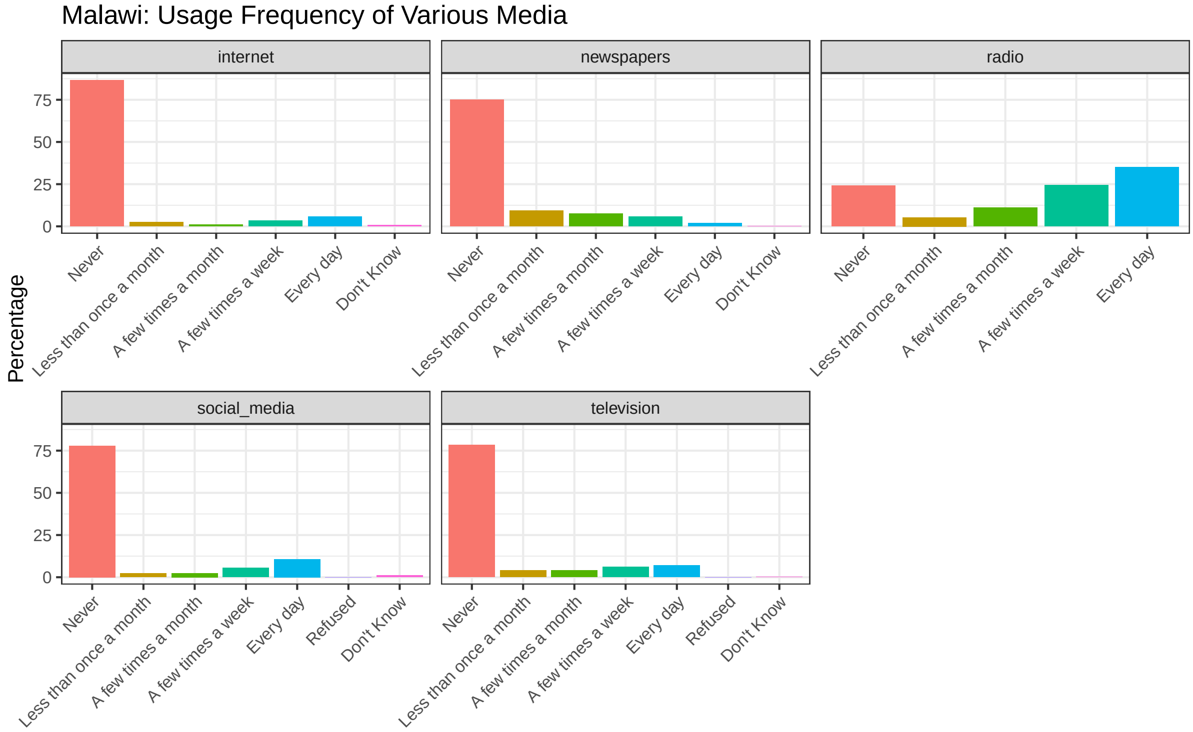
Figure 18: Media coverage. 2017-2024, Source: GDELT




*Notes: the timeline reports volume as a percentage of matching articles by the total number of all articles monitored by GDELT at each time step.*

Figure 18 displays the news coverage of the phrases "government preparedness" and "government relief" in the upper panels, and "disaster preparedness" and "disaster relief" in the middle panels, along with benchmark policies "taxation" and "unemployment". The plots on the left-hand side present the results for all countries in the dataset, while the plots on the right display the results specifically for Malawi. The X-axis represents the date, and the Y-axis represents the volume score, which essentially measures the volume of news coverage matching your query by day over the search period. Considering that the total number of news articles published globally varies significantly throughout the day, as well as during weekends and holiday periods, the API does not return a raw count of matched articles. Instead, it calculates the number of matching articles as a percentage of the total number of all articles monitored by GDELT at each time step. Thus, the timeline reports volume as a percentage of all global coverage monitored by GDELT. We observe that all phrases receive media coverage during the timeframe. However, regardless of the exact wording, disaster relief is consistently covered more often by the news media compared to disaster preparedness. In terms of magnitude, between 0.5% and 2% of articles include a phrase about "government relief", and between 0.2% and 0.5% of articles mention "disaster relief". The coverage of both preparedness phrases is significantly lower. This pattern also holds for the Malawi-specific analysis. The plots using data from Malawi also show face validity, as we observe significant peaks for disaster relief at the beginning of 2019 and 2023, coinciding with the years when two major cyclones hit the country. This evidence suggests that voters do indeed have access to information about preparedness and relief policies, but coverage is more focused on disaster relief. Comparing the disaster policy coverage to other policy areas reveals that unemployment is covered to a larger extent (between 1% and 4%, with a peak during the COVID-19 crisis), but coverage levels of taxation are similar to those of disaster policies (around 0.3%). However, in Malawi, disaster policies (especially relief) are covered very similarly to taxation and unemployment. One caveat is, however, that only a minority of respondents in Malawi rely on newspapers to inform themselves. Figure 19 displays data from Afrobarometer Round 8 and shows that most respondents use the radio as their primary source of information. Nonetheless, roughly 25% report that they do sometimes rely on newspapers for news. Additionally, previous research suggests that the topics covered by different media outlets are very similar. For example, Druckman (2005) finds that while the volume of news coverage varies significantly between television and newspapers, the content of the coverage does not show substantial differences. Maier (2010) finds similar evidence when comparing newspapers, network television, cable television, and radio. Therefore, we can conclude that voters do have access to information about disaster policies, but the coverage is heavily skewed towards reports about disaster relief.

Figure 19: Malawi: Usage Frequency of Various Media

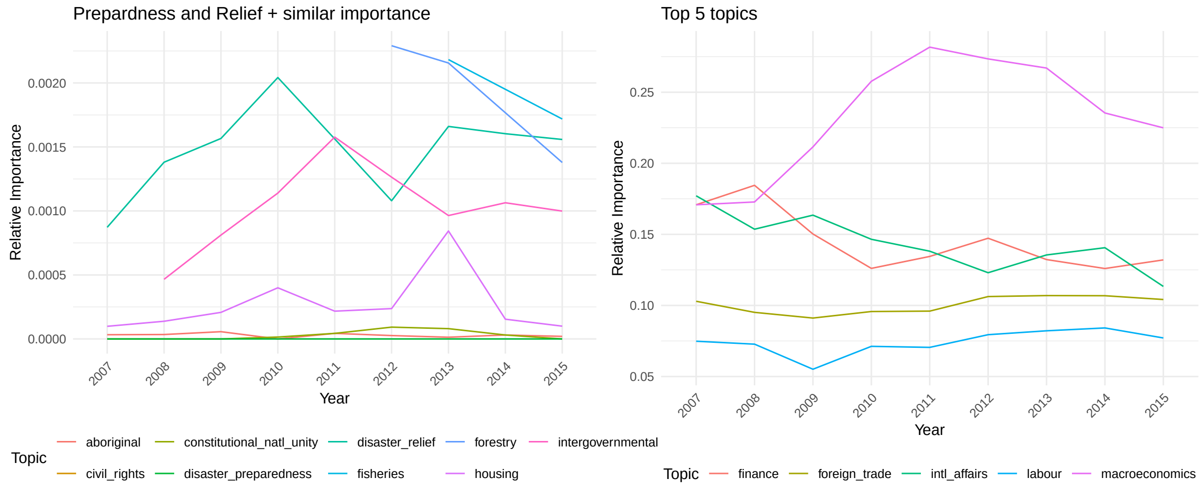



*Notes: Data from Afrobarometer round 8; question: "How often do you get news from the following sources?"*

### K.2 Political Speeches: disaster preparedness vs. disaster relief

Another source of information for voters about disaster policies is political speeches. To my knowledge, there is no publicly available dataset on speeches by African politicians, so I rely on the EUSpeech dataset (Schumacher et al. 2016), which collected 18,403 speeches from EU leaders (i.e., heads of government in 10 member states, EU commissioners, party leaders in the European Parliament, and leaders of the ECB and IMF) from 2007 to 2015. Speeches at the EU level are relevant because many natural disasters occur in several countries and necessitate coordinated preparedness and relief efforts. To measure policy agendas, I use the 'dictLexic2Topics' dictionary. In addition to the policy areas included in the dictionary, I add phrases related to preparedness and relief policies. Figure 20 presents the results. The left plot shows the relative importance of disaster preparedness and relief alongside similar policy topics. For comparison, the right plot shows the top 5 policy topics over time. The results suggest that disaster policies do not play a prominent role in EU political speeches. Topics around disaster relief have a similar prevalence in the speeches as intergovernmental issues and forestry matters. However, disaster preparedness is even less frequently featured. We can conclude that politicians are less likely to mention preparedness policies compared to relief policies.

Figure 20: EU Speeches: Relative importance of topics between 2007 to 2015




*Notes: Data from EUSpeech dataset."*

# References


Abramson, Scott F., Korhan Kocak, and Asya Magazinnik. 2022. "What Do We Learn about Voter Preferences from Conjoint Experiments?" *American Journal of Political Science* 66 (4): 1008–1020.

Bansak, Kirk, Jens Hainmueller, Daniel J. Hopkins, and Teppei Yamamoto. 2022. "Using Conjoint Experiments to Analyze Election Outcomes: The Essential Role of the Average Marginal Component Effect." *Political Analysis,* 1–19. https://doi.org/10.1017/pan.2022.16.

Bechtel, Michael M, and Jens Hainmueller. 2011. "How Lasting Is Voter Gratitude? An Analysis of the Short-and Long-Term Electoral Returns to Beneficial Policy." *American Journal of Political Science* 55 (4): 852–868.

Cavalcanti, Francisco. 2018. "Voters sometimes provide the wrong incentives. The lesson of the Brazilian drought industry." *Working Paper.*

Chen, Chen, Ian Noble, Jessica Hellmann, Joyce Coffee, Martin Murillo, and Nitesh Chawla. 2015. "University of Notre Dame global adaptation index country index technical report." *ND-GAIN: South Bend, IN, USA.*

Chinsinga, Blessings. 2005. "District assemblies in a fix: the perils of the politics of capacity in the political and administrative reforms in Malawi." *Development Southern Africa* 22 (4): 529–548.

Clarke, Daniel J, and Stefan Dercon. 2016. *Dull Disasters? : How Planning Ahead Will Make a Difference.* Oxford: Oxford University Press.

Cole, Shawn, Andrew Healy, and Eric Werker. 2012. "Do voters demand responsive governments? Evidence from Indian disaster relief." *Journal of Development Economics* 97 (2): 167–181.

Cooperman, Alicia. 2022. "(Un) Natural Disasters: Electoral Cycles in Disaster Relief." *Comparative Political Studies,* 1158–1197.

Druckman, James N. 2005. "Media matter: How newspapers and television news cover campaigns and influence voters." *Political communication* 22 (4): 463–481.

Ejdemyr, Simon, Eric Kramon, and Amanda Lea Robinson. 2018. "Segregation, ethnic favoritism, and the strategic targeting of local public goods." *Comparative Political Studies* 51 (9): 1111–1143.

Fair, C Christine, Patrick M Kuhn, Neil Malhotra, and Jacob N Shapiro. 2017. "Natural Disasters and Political Engagement: Evidence from the 2010–11 Pakistani Floods." *Quarterly Journal of Political Science* 12:99–141.

Gailmard, Sean, and John W Patty. 2019. "Preventing Prevention." *American Journal of Political Science* 63 (2): 342–352.

Gallego, Jorge. 2018. "Natural disasters and clientelism: The case of floods and landslides in Colombia." *Electoral Studies* 55:73–88.

Gasper, John T, and Andrew Reeves. 2011. "Make It Rain? Retrospection and the Attentive Electorate in the Context of Natural Disasters." *American Journal of Political Science* 55 (2): 340–355.

Guha-Sapir, Debarati, and Philippe Hoyois. 2015. "EM-DAT: The CRED/OFDA International Disaster Database." *Université Catholique de Louvain.*

Hainmueller, Jens, Daniel J Hopkins, and Teppei Yamamoto. 2014. "Causal Inference in Conjoint Analysis: Understanding Multidimensional Choices via Stated Preference Experiments." *Political Analysis* 22 (1): 1–30.

Healy, Andrew, and Neil Malhotra. 2009. "Myopic Voters and Natural Disaster Policy." *American Political Science Review* 103 (3): 387–406.

Kruczkiewicz, Andrew, H. Cen, B. Moneymaker, J. Lessel, R. Kufandiko, J. Pagona, E. Coughlan de Perez, A. Sweeney, and P. Ceccato K. Ndungu. 2016. *January 2015 Malawi Floods from a Remote Sensing Perspective.* Technical report. Accessed August 2021. 96th American Meteorological Society Annual Meeting, Working Paper. https://ams.confex.com/ams/96Annual/webprogram/Paper291189.html.

Leeper, Thomas J, Sara B Hobolt, and James Tilley. 2020. "Measuring subgroup preferences in conjoint experiments." *Political Analysis* 28 (2): 207–221.

Leetaru, Kalev, and Philip A Schrodt. 2013. "Gdelt: Global data on events, location, and tone, 1979–2012." In *ISA annual convention,* 2:1–49. 4. Citeseer.

Legerski, John-Paul, and Sarah L Bunnell. 2010. "The risks, benefits, and ethics of trauma-focused research participation." *Ethics & Behavior* 20 (6): 429–442.

Lust, Ellen, Adam Harris, Kristen Kao, Pierre Landry, Boniface Dulani, Atusaye Zgambo, Asiyati Chiweza, et al. 2016. "The local governance performance index (lgpi) Malawi truncated dataset." *Program on Governance and Local Development - University of Gothenburg.*

Maier, Scott. 2010. "All the news fit to post? On the Web to newspapers, television and radio comparing web content." *Journalism & mass communication quarterly* 87 (3-4): 548–562.

Mani, Anandi, Sendhil Mullainathan, Eldar Shafir, and Jiaying Zhao. 2013. "Poverty Impedes Cognitive Function." *science* 341 (6149): 976–980.

Pauw, Karl, James Thurlow, Murthy Bachu, and Dirk Ernst Van Seventer. 2011. "The economic costs of extreme weather events: a hydrometeorological CGE analysis for Malawi." *Environment and Development Economics* 16 (2): 177–198.

PDNA-Report. 2015. *Malawi 2015 Floods Post Disaster Needs Assessment Report.* Technical report. Government of Malawi, April.

Peratsakis, Christian, Joshua Powell, Michael Findley, Justin Baker, and Catherine Weaver. 2012. "Geocoded activity-level data from the government of Malawi's aid management platform." *Washington DC AidData and the Robert S. Strauss Center for International Security and Law.*

Robinson, Amanda Lea. 2016. "Internal Borders: Ethnic-Based Market Segmentation in Malawi." *World Development* 87:371–384.

Schumacher, Gijs, Martijn Schoonvelde, Denise Traber, Tanushree Dahiya, and Erik De Vries. 2016. "EUSpeech: A new dataset of EU elite speeches."

The Nation. 2015. *Mulanje develops disaster response plan.* The Nation. https://mwnation.com/mulanje-develops-disaster-response-plan/.