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Collective Shocks and Social Preferences: A Global, Subnational Analysis

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Abstract
While some studies of conflicts, natural disasters, and economic setbacks find these negative collective shocks make people more prosocial, others find they reduce cooperation. These conflicting findings may be a consequence of focusing on a single shock type, a single preference measure, or a single regional or temporal context experiencing shocks. We address these limitations by creating and analyzing a new global dataset of collective shocks and social preferences at the subnational level. We then explore the potential differences in how various shocks (armed conflicts, natural disasters, economic downturns) relate to various social preferences (altruism, reciprocity, trust) and behaviors. Our preliminary analysis shows that, while exposure to armed conflicts or economic downturns does not systematically alter prosociality, exposure to natural disasters reduces some social preferences in the short term, reverting to baseline levels in the long term. By comparing local experiences globally, our project helps develop a nuanced view of how shocks influence preferences, with implications for cooperation and governance.

Keywords
Natural Disasters, Armed Conflicts, Altruism, Reciprocity, Trust

JEL Classifications
D64, D74, Q54

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Social scientists increasingly recognize the powerful influence of social preferences, understood as concern for the well-being of others, on many important behaviors and attitudes. Social preferences impact individual decisions to cooperate with others, to contribute to public goods, and to help those in need. Influential work across fields, including economics (Fehr and Fischbacher, 2002), political science (Dawes et al., 2011), and psychology (Kahneman and Tversky, 2000), now regularly analyzes social preferences.

Social preferences can be organized along three key dimensions: preferences over outcomes, the role of intentions and process, and the identity of the target. The most fundamental dimension of social preferences concerns how an individual values the final distribution of resources. This can be conceptualized as a simple range from altruism (a positive weight on others' payoffs), to pure selfishness (a zero weight), to spite (a negative weight). More complex models of inequity aversion formalize the common observation that people have an intrinsic dislike for unequal outcomes. Two foundational models capture this idea in distinct ways (Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999) and explain why people might sacrifice their own payoff to achieve more equitable outcomes, a behavior consistently observed in experiments (Güth et al., 1982).

Social preferences can also be defined by the perceived intentions behind an action. This category of process-based preferences includes reciprocity and trust. Reciprocity is a conditional response to the perceived kindness or hostility of others' actions (Rabin, 1993). It dictates that individuals should reward kind actions and punish unkind ones, even at a personal cost and with no expectation of future interaction (Fehr and Gächter, 2000). Trust is another important process-based preference, defined as a belief that another person will act in a way that is beneficial, or at least not detrimental, to one's own interests. Societies with higher levels of interpersonal trust exhibit better social and economic outcomes (Putnam, 2000; Sønderskov, 2011). This is because the general expectation of cooperation encourages more cooperation in turn.

The expression of social preferences is not uniform across targets. Instead, this can depend on the degree to which salient social identities align with or differ from those

of the target (Tajfel et al., 2001). Parochialism describes prosociality that is directed toward in-group members, sometimes accompanied by hostility toward outsiders (Choi and Bowles, 2007). In contrast, a universalist preference is an impartial concern for others, irrespective of their group affiliation. Much research, including this paper, measures social preferences in a universalist context, where participants make decisions affecting anonymous, unspecified others. By neutralizing in-group and out-group dynamics, such designs are useful for understanding the many economic and social interactions that occur between strangers in modern societies. The universalist approach also provides a crucial benchmark against which group-based effects can be compared.

An important body of research argues that social preferences can be reshaped by collective, negative shocks such as wars, natural disasters, and economic recessions (Bruhin et al., 2018; Chuang and Schechter, 2015; Giuliano and Spilimbergo, 2025). The literature, however, presents a puzzle, as the direction of these changes is inconsistent across studies. Research on armed conflict, for instance, offers a range of findings. Some studies find that exposure to violence enhances universal prosociality, proposing mechanisms such as post-traumatic growth (Blattman, 2009; Canevello et al., 2022), empathy born of suffering (Hartman and Morse, 2020), and social insurance against future shocks (Bauer et al., 2016). Other studies find that conflict erodes generalized trust (Kijewski and Freitag, 2018; Walsh et al., 2024) and that any increase in cooperation is parochial—limited to one's in-group—rather than universal (Bauer et al., 2016). The evidence is similarly divided for natural disasters. Some studies report an increase in generalized trust and cooperation after disasters, suggesting that shared adversity can strengthen social bonds (Cassar et al., 2017; Toya and Skidmore, 2014). However, other research finds that disasters can decrease social trust, particularly when the event is severe, the government response is inadequate, or competition over scarce resources intensifies (Albrecht, 2018; Vardy and Atkinson, 2019a). In contrast, research on economic shocks has often pointed to a negative relationship between exposure and social preferences, with studies finding that experiencing a recession correlates with a lasting reduction in universal pro-sociality (Fisman et al., 2015).

One reason for these inconsistent findings is that most research is limited in scope. Studies often examine one broad category of shock (such as disasters) and not infrequently investigate a single type of shock (such as earthquakes) or a single episode of a shock (such as the 2017 earthquake in Mexico City). There have been few efforts to investigate if different categories of shocks have distinct effects on social preferences. Furthermore, studies often investigate a single form of prosocial preferences, leaving unanswered the question of if shocks have similar consequences for different preferences. Finally, research is frequently carried out in a single country or setting. While such a research design is motivated by the goal of better identifying causal effects, one consequence is that we have little sense of if findings cumulate across settings.

Resolving these contradictions requires a more comprehensive empirical approach to understanding if exposure to shocks has an effect on social preferences, or if such preferences are largely set and do not change much in response to shocks. This paper addresses three central questions: First, how consistent is the relationship between shocks and universal preferences across different settings? Second, do different types of shocks have distinct effects on universal social preferences? Third, do these shocks produce uniform or varied effects across different dimensions of social preferences, such as trust and altruism?

We address these questions by creating and analyzing a global, subnational dataset that integrates three types of collective shocks—armed conflicts, natural disasters, and economic downturns—with multiple measures of social preferences at the subnational level across many countries.

We construct a global dataset by merging data at the level of first-level administrative (ADM1) regions. Our data comes from three primary sources: the Global Preference Survey (GPS) module of the Gallup World Poll (GWP), the Geocoded Disasters extensions of the EM-DAT International Disaster Database (GDIS), the Uppsala Conflict Data Program's Georeferenced Event Dataset (GED), and the Subnational Human Development Index (SHDI). The GPS provides data on people's prosocial preferences, which serve as our outcome variables, and individual-level covariates. The GDIS, GED, and SHDI provide data for our treatment variables of exposure to disasters, conflicts, and economic

downturns. We also control for three ADM1 characteristics–area, population, and income per capita.

The GWP consists of annual surveys conducted in dozens of countries using nationally representative samples. We use data from the 2012 wave of the World Poll, which included 76 countries that vary in terms of political systems, cultures, and levels of development. The 2012 wave of the GWP is the only one to include the GPS module (Falk et al., 2018). The GPS collects comparable cross-national data on risk, time, and social preferences, and is, to the best of our knowlege, the most comprehensive attempt to measure such preferences across settings. GPS measures of social preferences, described below, are our main outcome variables. Additional survey items in the GWP measure self-reported prosocial behaviors. We combine these measures in an index and use as an additional outcome variable. The Gallup World Poll also includes various demographic items that we use as individual-level control variables.

Empirical Strategy

Gallup identifies the location of each respondent at the level of the first order administrative district. We use this unit to match the location of the respondent when the survey was administered to the locations where disasters and conflicts occurred. The GWP sometimes uses non-standard identifiers of subnational units for some countries. This paper drops the subnational units with these identifieres. We are in the process of reconciling these units to a common standard compatible with the EM-DAT, GED, and SHDI data. Our current matched dataset includes 71 countries, 1006 first-order administrative districts, and 69,271 respondents.

The resulting dataset has a number of advantages for addressing our three research questions. The first is scale. Many studies of the relationships between shocks and preferences focus on a single country, or a region within a country, whose residents or communities experience variation in exposure to a particular shock. This approach can have a number of strengths, such as drawing on case- or country-specific expertise to determine the de-

gree to which a shock is exogenous and to control for context-specific factors that might influence the outcome. Our dataset complements these studies' by including many more countries, subnational regions, and respondents whose preferences are measured with a common instrument. This scale puts us in a better position to estimate the overall relationship between shocks and preferences. Second, our dataset includes measures of three types of shocks, allowing us to estimate if different types of shocks have distinct relationships with social preferences. Third, the GPS measures multiple social preferences, allowing us to determine if shocks influence different preferences in the same way.

The data we assemble has two principal weaknesses. First, it is possible that not all locations in a subnational (ADM1) region will experience the a shock or experience it to the same extent. A cyclone, for example, may do great damage to the coastal area of a subnational region but have little direct effect on deep interior areas. This is likely to understate the degree to which shocks influence social preferences, although we cannot estimate how much bias this will introduce. We seek to address this by including as covariates three characteristics of administrative districts–area, population density, and income per capita. Second, we measure respondents' preferences at a single point in time. This means that we can only estimate the relationship between experiencing shocks and preferences across but not within individuals.

Outcome Variables

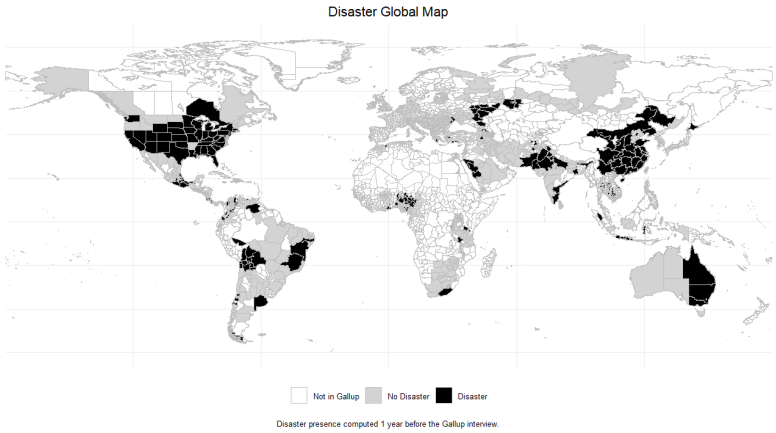
For our outcome variables, we use the GPS measures of three distinct social preferences that span the first two dimensions outlined in the introduction. These are positive reciprocity, altruism, and trust. We also analyze self-reported prosocial behaviors. Positive reciprocity and altruism are each measured with two survey items combined using weights developed during the validation of the GPS. *Positive reciprocity* is the willingness to pay a cost to return a favor. The first GPS item measuring positive reciprocity is a self-assessment of willingness to return a favor. The second is a quantitative scenario in which the respondent receives help from a stranger, and chooses to give the stranger a hypothetical present. The value of the present is the measure of positive reciprocity for

this item. *Altruism* is the willingness to pay a cost to help others. The first altruism item is a self-assessment of willingness to give to good causes. The second is a quantitative scenario in which the respondent unexpectedly receives the equivalent of 1000 euros, and is asked how much of this hypothetical windfall they would donate. The amount donated is the measure of altruism for this item. *Trust* is based on a single item that asks respondents if they believe that other people only have the best intentions (Falk et al., 2018).

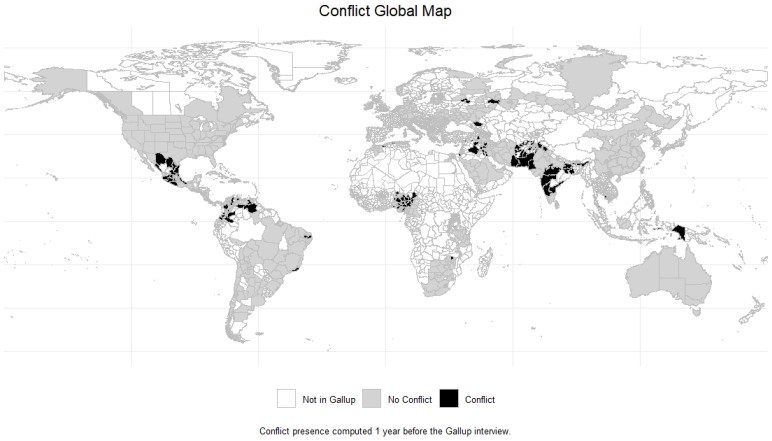
The GPS prosocial preference measures above are based on self-assessments of behavior in hypothetical situations. We complement these measures with GWP's regular self-reported prosocial behavior items. The resultant additive *prosocial behavior index* consists of the three binary questions previously used in the initiatives like the CAF World Giving Index to compare prosociality across countries. The first question asks if the respondent has helped a stranger, the second if the respondent has volunteered time to help a charitable organization, and the third if people donated *over the past year*. The advantage of this measure is that it captures self-reported but potentially actual, not just hypothetical, prosocial behaviors. The disadvantage is that it is arguably more vulnerable to social desirability bias and is also more a function of opportunities to help that are endogenous to shocks over a specific, *year-long* time period.

Treatment Variables

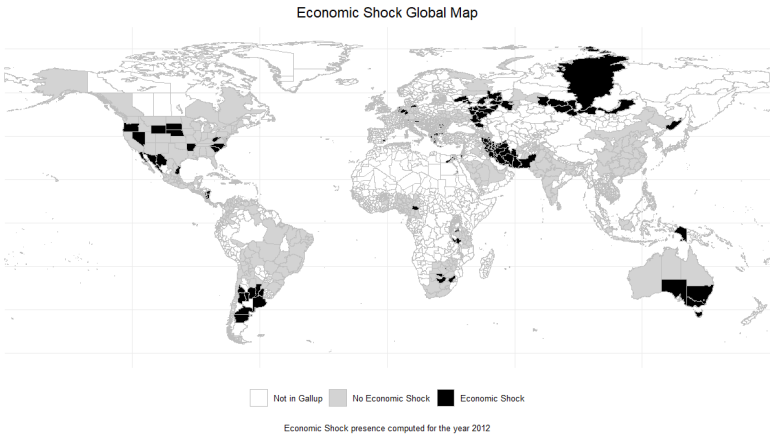
We conceive of negative collective shocks as changes in the social, economic, or physical environments that undermine physical survival, livelihood, and social networks. Our focus is on *collective* shocks, which impact entire communities in a detrimental way. We distinguish such collective shocks from those that affect individuals or small groups, such as being the victim of violent crime or a fire that destroys a family's dwelling. We also focus on *negative* shocks since they have a larger potential to impact preferences than positive shocks (Passarelli and Del Ponte, 2020). Although such negative collective shocks can take many forms, in this paper, we focus on wars, natural disasters, and economic downturns.



(a) Subnational localities that experienced a disaster in 2011-2012



(c) Subnational localities that experienced a conflict in 2011-2012



(d) Subnational localities that experienced an economic shock in 2011-2012

Figure 1: Spatial Distribution of Treatment and Outcome Variables

Our primary treatment measures are binary variables and counts of natural disasters, conflicts, and economic recessions recorded in the subnational region where each respondent lives that took place within 90/365 days (3/12 months) prior to the interview date. We use different temporal lags to ensure our results are not a result of the use of a particular time period (e.g., Lewis and Topal, 2023), as well as compare the potential short-term and longer-term effects. Due to data availability issues, we measure economic downturns over the annual period only.[1] We visualize the geographic distribution of our main shock variables in Figure 1.

Natural Disasters

Our source for natural disaster shocks is the EM-DAT dataset (CRED/UCLouvain, 2024). We use the version of the data that has been systematically geocoded (Rosvold and Buhaug, 2021). The unit of analysis in EM-DAT is the disaster. EM-DAT defines disaster as hazards that produce at least 10 deaths, affect at least 100 people, or lead to a declaration of a state of emergency or a request for international assistance. Our measurement of the treatment variable includes information on the following types of disasters: earthquakes, volcanic activity, floods, landslides, storms, extreme temperatures, droughts, and wildfires. In the main models reported in the paper, this treatment variable is a dichotomous measure that takes a value of 1 if any disaster has occurred in the subnational region where their respondent resides in the N days prior to the interview date. Measuring disaster exposure as a dummy variable has the advantage of being comparable to our measures of exposure to war and economic recessions. However, it does not measure the frequency of disasters. We might expect that more frequent disasters would change the relationship to the outcome variables. To investigate if this is the case, in the appendix we report models where disasters are measured as the (log) number of disasters

[1]To better align our model with the prosocial behavior index, which references actions from the year prior to the interview, we made two key adjustments to our main specification (see Tables A3 and A5). First, we extended the conflict and disaster exposure windows from 3 and 12 months to 12-15 and 12-24 months before the interview, ensuring alignment with the survey's retrospective timeframe. Second, we revised the historical shock variables to span 10 to 2 years before the interview, maintaining a clear distinction between long-term historical effects and more recent exposures captured by our treatment variables.

a subnational region experienced within a certain period. Additionally, we include an alternative specification that uses disaster-related fatalities as a proxy for disaster intensity. Fatalities are converted to rates per 100,000 inhabitants, log-transformed to reduce right-skewness, and rescaled to range from 0 to 1. Results are reported in the Appendix.

Armed Conflicts

Our source for exposure to wartime violence is the GED (Sundberg and Melander, 2013). The unit of analysis in the GED is a violent wartime event. It includes events that involve the use of armed force by at least one organized combatant and that result in at least on fatality. The GED includes information on the subnational location where each event occurs, which we match to our outcome variables. The GED classifies each violent wartime events into one of three categories. A state-based event involves armed conflict between government forces and an organized, armed group. A non-state event involves conflict between two non-state armed groups. One-sided violence is coded when government forces or an organized, armed group use lethal violence against civilians.

In our main models, we measure the treatment variables for exposure to wartime violence as a dummy variable that takes a value of 1 if the subnational region in which the respondent resides experienced any violent event recorded in the GED in the N days prior to the interview date. As with our measures of exposure to disasters, in the appendix, we also report models where the measure of exposure to wartime violence is a log of events over the previous N days.

In models reported in the appendix, we also break out exposure to separately measure exposure to state-based and one-sided violence during the same time windows.[2] We expect that exposure to one-sided violence has a stronger relationship to prosocial preferences than will exposure to battles. Deliberate targeting of civilians can galvanize communities and increase social cohesion. Civilians who witness or learn about such violence may develop stronger bonds with each other as a response to shared threats and suffering, and band together to effectively aid each other and to resist future violence (Kalyvas,

[2]We exclude non-state conflict events as these comprise only a small percentage of all conflict events.

2006; Kaplan, 2017; Wood, 2003).

Additionally, we include an alternative specification that uses conflict-related fatalities as a proxy for conflict intensity. Fatalities are converted to rates per 100,000 inhabitants, log-transformed to reduce right-skewness, and rescaled to range from 0 to 1. Results are reported in the Appendix.

Our measure of economic output shocks is derived from the income component of the Subnational Human Development Index (SHDI), which provides standardized measures of economic development across regions (Smits and Permanyer, 2019). We operationalize economic shocks by examining year-over-year changes in the income index at the subnational level, specifically focusing on the 2011-2012 period. Regions experiencing a negative GDP per capita growth rate between these years are classified as having undergone an economic downturn shock or a negative GDP shock, which we capture through a binary indicator variable.

This approach enables the systematic identification of economic shocks using the best available subnational data but has limitations. The annual measurement window may miss rapid economic shocks occurring within shorter timeframes or brief yet severe disruptions followed by swift recovery.

Individual Covariates

Our analyses include controls for the following basic individual-level covariates: age, marital status, education level, gender, income quantile, employment status, and residential area (farm, village, suburb, city). These data are from the GWP.

ADM1 Covariates

We also control for a number of characteristics of our subnational spatial units. Population was primarily sourced from the Subnational Geospatial Data Archive (Kollman and Zhukov, 2023). For countries with missing data, we supplemented information from national statistical institutes, prioritizing data closest to the year 2012. Geographic ar-

eas were calculated using the Natural Earth shapefiles (Earth, 2023) and converted to square kilometers. In cases where data remained unavailable from primary sources, we utilized information from administrative unit websites, the Encyclopedia Britannica, or Wikipedia. We control for regional wealth with the log of gross national income per capita for each ADM1 unit measured in 2011 US dollars with purchasing power parity (Smits and Permanyer, 2019). Where necessary, linear interpolation between years and linear extrapolation for periods up to three years were applied to complete these variables in our dataset.

Subnational locations are not equally likely to experience the same shocks. For example, coastal locations are more likely to experience hurricanes, and civil conflicts are more likely to break out in areas that have experienced civil war in the past (Walter, 2015). Past experience with shocks may influence the relationship between shocks and preferences. For example, a region that regularly experiences hurricanes might have developed physical infrastructure that mitigates the negative consequences of storms. This, in turn, might moderate the contemporary relationship between a hurricane and social preferences. To account for this possibility, in some specifications we include a count of the number of disasters or conflicts that occurred in the 9-year period prior to the interview date, excluding the year immediately preceding the interview to avoid overlap with the treatment variables.

Additionally, we account for historical economic conditions by calculating the average change in the income index over the nine years prior to the treatment year, excluding the treatment year itself, for each location.

Estimation

Our unit of analysis is the respondent in 2012 (N = 69,271). Respondents are located in ADM 1 sub-national regions (N = 1006), which is the level at which the treatments are measured. Respondents and regions are nested within countries (N = 71). When estimating the between-respondent effects of the treatment on the outcome variables, we use

OLS regressions with individual-level covariates to account for individual-specific factors, ADM1 characteristics to control for factors within subnational regions, and country fixed effects to account for country-specific factors. Standard errors are clustered at the treatment level (ADM1). We utilize survey weights in every model. For easier interpretation, all independent variables were rescaled to vary from 0 to 1 unless specified otherwise. To make the effect magnitudes more comparable across treatments and outcomes, all our dependent variables were standardized (with a mean of 0 and a standard deviation of 1). For descriptive statistics, see Table A1.

Each model analyzes the relationship between the treatments (natural disasters, wartime violence, recessions) and one of the four response variables (positive reciprocity, altruism, trust, prosocial behaviors). We report four models for each of these eight relationships. The first includes only the treatment and country fixed effects. The second adds to this individual covariates. The third adds to this ADM1 covariates. The fourth adds to this shock history.

The Most Plausible Heterogeneous Effects by Age

Regardless of the overall relationship between negative collective shocks and social preferences, individuals are likely to be affected differently by disasters and conflicts based on various individual and contextual factors. In this paper, we test the single most plausible source of effect heterogeneity at the individual level as identified in the literature by interacting our shock treatments at the *adm1* level with the individual level binary indicators for young age.

The "impressionable years" theory from political socialization literature posits that preferences are more malleable during young adulthood but crystallize with age. Therefore, if shocks impact preferences, this impact should be greater among younger individuals (e.g., Kustov et al., 2021). Specifically, older adolescents and young adults are developing their core preferences and attitudes, making them more responsive to negative collective shocks. To test this while maximizing statistical power, we interact the treatment variable with a binary indicator for younger individuals (25 or younger) versus older individuals

(26 or older).[3]

Results

Figure 2 summarizes the results of the main specifications, which use dichotomous measures of exposure to disasters, conflicts, and economic downturns as the treatment variables. Full numerical results are available in Table A2.

We report additional results that vary how treatments and outcomes are measured in the appendix. Results from these specifications are qualitatively consistent with those reported in Figure 2 and Table A2. These include:

- Models that are identical to those reported in Table A2, but that use the prosocial behavior index as the outcome (Table A3).
- Models that are identical to those reported in Tables A2 and A3, but that interact respondent age with treatment variables (Tables A4 and A5).
- Results from models that vary the lag between exposure to a shock and measurement of the outcome variable. The models in Tables A2-A5 report lags of 3 and 12 months. We report only figures that summarize these results. Figures A1-A4 report models where the lags are 3, 6, 9, and 12 months. The treatments in these models are exposure to disasters, conflicts, state-based conflicts, and one-sided conflicts.
- Models that are identical to those reported in Table A2, but that measure exposure as the logged number of disasters or conflicts that occurred over the previous 3 or 12 months. We report only figures that summarize these results. Figure A5 reports models using the logged number of disasters as the treatment variable, and Figure A6 those using the logged number of conflicts.
- Models that are identical to those reported in Table A2, but that measure exposure as the logged number of causulties caused by disasters or conflicts that occurred over the previous 3 or 12 months. We report only figures that summarize these results.

[3]We also considered alternative age thresholds with no change in underlying results (not shown).

Figure A6 reports models using the logged number of disasters as the treatment variable, and Figure A7 those using the logged number of conflicts.

For conflicts, there appears to be no general systematic relationship between exposure to shocks and social preferences. All of the coefficients on the exposure to wartime violence are statistically indistinguishable from zero. This pattern is consistent across models that include shocks over longer and shorter time windows, and that include different sets of control variables. It is also the case when exposure to conflict is interacted with respondent age.[4]

The results for economic shocks similarly suggest a generally weak and inconsistent relationship with social preferences. Across most outcome variables and model specifications, the coefficients for annual GDP per capita declines are mostly negligible. One notable exception is a statistically significant negative association between these economic shocks and prosocial behaviors over the past year, suggesting that economic downturns may discourage broader social cooperation as individuals face constrained time and resources. Nevertheless, the lack of consistent patterns across models indicates that the overall impact of economic downturns on prosociality is likely minimal in our data.

Turning to natural disasters, exposure may impact some social preferences, at least in the short term. In particular, we see that residing in a region experiencing a disaster in the previous 3 months is consistently associated with reduced positive reciprocity and altruism across different models. At the same time, natural disaster occurrence has null relationships with trust and self-reported prosocial behaviors. The results from models that use a measure of the intensity of the consequences of disaster exposure, measured as the logged number of deaths that result from disasters, show a negative relationship between deaths and altruism only (see Table A6). The magnitude of the associations

[4]One exception to our findings is that exposure to one-sided violence is associated with heightened altruism, consistent with existing literature on war and cooperation (Bauer et al., 2016). However, we suggest that, overall, exposure to war does not influence social preferences based on our data and research design. If war exposure increased prosociality, it is unclear why this effect appears only for altruism and not other outcome variables. Moreover, this positive relationship is one among eight related models that vary the treatment measurements (battles or one-sided violence) and the outcomes (positive reciprocity, altruism, trust, and prosocial behaviors), suggesting it may be due to chance.

with the first two outcome variables is meaningful. The coefficients on (standardized) positive reciprocity and altruism (-0.11-0.16) are comparable to those with education and are considerably larger than the association with gender, which prior research has found to be a consistent predictor of prosocial attitudes (Falk et al., 2018).

This finding of a negative association between disaster exposure and prosociality stands in contrast to much of the research in this area, which posits that collective adversity should prompt increased prosociality (Rose et al., 2022; Steimanis and Vollan, 2022). Instead, it is consistent with the idea that "disasters reduce cooperation by motivating individuals to prioritize short-term needs over the more diffuse and long-term benefits of relationship building and cooperation" (Vardy and Atkinson, 2019b). This perspective is consistent with our finding that disasters are associated with reductions in some measures of prosociality, but only in the short run. It suggests that, in the immediate aftermath of a disaster, people focus on their immediate personal needs. As these needs are met, they revert to their prior, baseline levels of prosociality. Natural disasters may influence prosociality, but only in the short run, an idea that is consistent with the findings is that social preferences are largely stable over the course of life.

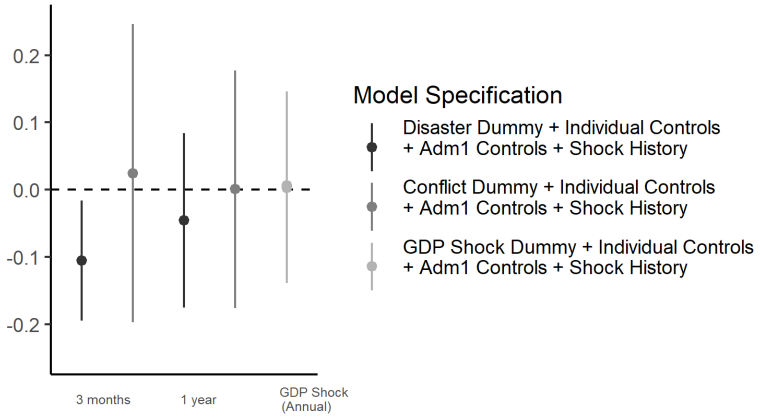
Table A4 and A5 also present models where exposure to natural disasters is interacted with the respondent's young age (1 if 25 or below). The results generally do not align with the "impressionable years" hypothesis, showing that most effects are not statistically different among the younger and the older respondents.

Discussion

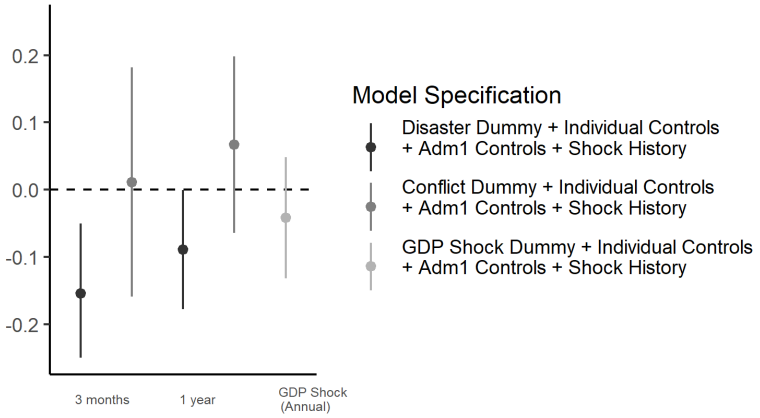
This paper contributes to the literature on how negative collective shocks influence social preferences by analyzing a new global dataset of conflicts, natural disasters, economic downturns, and prosocial attitudes at the subnational level. Our analysis reveals no consistent relationship between exposure to violent or economic shocks and social preferences. We find that natural disasters, in the short run, are associated with lower levels of positive reciprocity and altruism, but this effect dissipates over time. These findings stand in

Figure 2: Collective Shocks and Social Preferences by Exposure Time

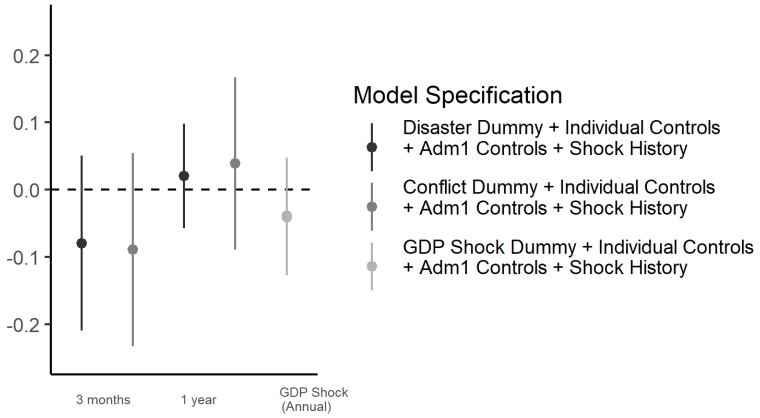
(a) Positive Reciprocity



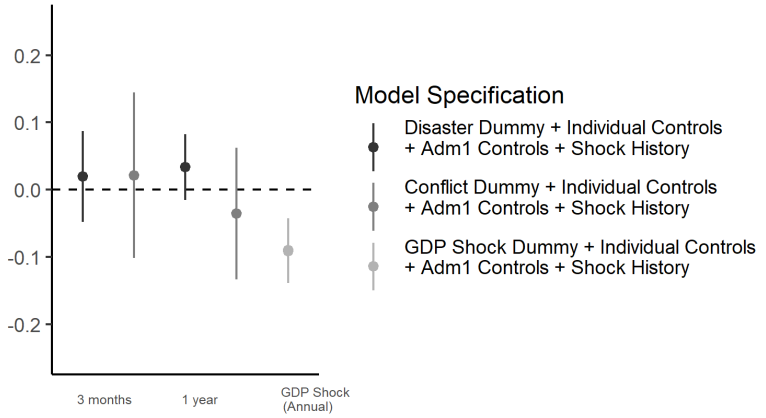
(b) Altruism



(c) Trust



(d) Prosocial Behavior Index



Notes: All coefficients are estimated using OLS specifications as shown in Table A2. All outcome variables are standardized, and all treatment variables are binary. Standard errors are clustered at ADM1 level, and country fixed effects are employed, in all models.

contrast to much existing research that reports both positive and negative relationships between shocks and preferences. Our null results for conflict exposure and time-limited negative effects of disasters are consistent with the idea that social preferences, once formed, are largely stable over time.

Our findings have important implications for future research on shocks and preferences. They suggest that scholars should focus less on estimating general relationships between these phenomena and more on identifying the contextual factors that might moderate how shocks influence preferences. For example, the ethnic or religious composition of communities experiencing conflict could shape how exposure to violence influences preferences. Our research design, which combines individual-level survey data with spatial information on shocks, across settings provides a template for testing such conditional hypotheses.

A valuable aspect of our research design is that it allows us to directly compare the consequences of different types of shocks. We find that war, economic downturns, and disasters have distinct effects on preferences. Why might this be the case? A number of explanations are plausible and could be investigated further. One is that these shocks unfold over different time scales, which could have a range of implications for preferences. Violent wartime events are often preceded and followed by long periods of political tension. Natural disasters frequently have shorter durations and create more immediate shock and disruption. The null effect of wartime violence might reflect a longer-term equilibrium in which individuals' prosociality has had an opportunity to revert to baseline levels. The short-term negative effect of disasters might reflect their more sudden onset, which results in a more immediate effect on social preferences. Similarly, resource scarcity may increase sharply when an economic downturn or natural disaster strikes but unfold more gradually during wartime and provide an opportunity to return to baseline levels. Communities experiencing wartime violence may develop coping mechanisms over time that maintain levels of prosociality. The persistence of the threat might lead to a "normalization" of the situation, where social behaviors remain relatively stable as a survival strategy.

A different explanation is that wars and natural disasters create quite distinct attributions of cause and control. Natural disaster victims might experience a sense of helplessness against impersonal forces, potentially reducing faith in social cooperation. In war and economic setbacks, there may be a clearer sense of human agency, allowing people to maintain beliefs in the efficacy of social action and cooperation. This would be consistent with the argument that exposure to wartime violence increases parochial prosociality, in which individuals adopt more prosocial behaviors and attitudes towards ingroup members (Bauer et al., 2016). Exposure to war might lead people to be more prosocial to ingroup and less prosocial to outgroup members, producing a net effect that is near zero.

Future work could also profitably investigate the mechanisms linking shocks to preferences. Our finding that natural disasters reduce some forms of prosociality in the short run is consistent with the idea that people prioritize immediate personal needs in crisis situations. However, we cannot test this mechanism directly. Collecting data on how people perceive threats to their well-being and how they prioritize different needs could help illuminate why shocks influence preferences in some situations but not others. This work could draw on psychological theories of threat perception and coping to develop more nuanced accounts of how people respond to collective adversity.

Our study has several limitations that should be considered when interpreting our results. First, our treatment assignment at the first-level administrative unit may introduce measurement error, as exposure to shocks can vary within these units despite controls for territory size and population. Furthermore, the use of cross-sectional data restricts our ability to measure changes over time. Despite these constraints, our study offers valuable insights into the relationship between collective shocks and social preferences. By employing a global dataset and rigorous analytical methods, we contribute to a more nuanced understanding of how conflicts and natural disasters can influence prosocial attitudes. Our findings underscore the complexity of human responses to adversity and the need for continued research in this area.

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Appendix

Tables and Figures

Table A1: Descriptive Statistics

Dependent Variables	N	Mean	SD	Min	Max
Prosocial Outcomes (GPS):					
Positive Reciprocity	69181	0.00	1.00	-3.81	1.33
Altruism	68937	0.00	1.00	-2.60	2.33
Trust	67975	0.00	1.00	-1.96	1.68
Prosocial Behavior Index	69271	0.00	1.00	-1.31	1.82

Independent Variables	N	Mean	SD	Min	Max
All Disasters (EM-DAT):					
Disaster within 3 months	69271	0.06	0.23	0.00	1.00
Disaster within 6 months	69271	0.14	0.35	0.00	1.00
Disaster within 9 months	69271	0.22	0.41	0.00	1.00
Disaster within year	69271	0.29	0.45	0.00	1.00
Disaster within 12-15 months	69271	0.05	0.23	0.00	1.00
Disaster within 12-24 months	69271	0.30	0.46	0.00	1.00
All Conflicts (GED):					
Conflict within 3 months	69271	0.06	0.24	0.00	1.00
Conflict within 6 months	69271	0.08	0.27	0.00	1.00
Conflict within 9 months	69271	0.10	0.29	0.00	1.00
Conflict within year	69271	0.10	0.30	0.00	1.00
Conflict within 12-15 months	69271	0.08	0.27	0.00	1.00
Conflict within 12-24 months	69271	0.13	0.33	0.00	1.00
State Based Conflict (GED):					
State Conflict within 3 months	69271	0.04	0.20	0.00	1.00
State Conflict within 6 months	69271	0.06	0.24	0.00	1.00
State Conflict within 9 months	69271	0.07	0.26	0.00	1.00
State Conflict within year	69271	0.08	0.26	0.00	1.00
One Sided Violence (GED):					
One Sided Conflict within 3 months	69271	0.03	0.18	0.00	1.00
One Sided Conflict within 6 months	69271	0.04	0.21	0.00	1.00
One Sided Conflict within 9 months	69271	0.06	0.24	0.00	1.00
One Sided Conflict within year	69271	0.06	0.24	0.00	1.00
Economic Shocks (HDI):					
Negative GDP change Dummy (2012)	64505	0.24	0.43	0.00	1.00

Control Variables	N	Mean	SD	Min	Max
Individual Controls (GPS):					
Age	69054	0.31	0.20	0.00	1.00
Married	69271	0.54	0.50	0.00	1.00
Education	68983	0.42	0.33	0.00	1.00
Female	69271	0.55	0.50	0.00	1.00
Income Quantile	67863	0.56	0.35	0.00	1.00
Employed	69271	0.52	0.50	0.00	1.00
Village	68174	0.29	0.46	0.00	1.00
Suburb	68174	0.10	0.30	0.00	1.00
City	68174	0.34	0.47	0.00	1.00
Adm1 Controls:					
Logged Population	69113	0.05	0.12	0.00	1.00
Logged Area (Km2)	69113	0.03	0.09	0.00	1.00
Income Index (Adm1)	63398	0.55	0.25	0.00	1.00
Shock history (EM-DAT & GED):					
Logged Disaster History (9 years)	69271	0.24	0.24	0.00	1.00
Logged Conflict History (9 years)	69271	0.72	1.48	0.00	1.00
Average GDP change (9 years)	64505	0.39	0.15	0.00	1.00
Logged Disaster History (8 years)	69271	0.23	0.24	0.00	1.00
Logged Conflict History (8 years)	69271	0.10	0.20	0.00	1.00
Average GDP change (8 years)	64505	0.43	0.15	0.00	1.00

Table A2: Shock Exposure and Prosocial Outcomes

	Dependent Variables:					
	Positive Reciprocity		Altruism		Trust	
Disaster Dummy (3 months)	−0.105*		−0.158**		−0.080	
	(0.046)		(0.054)		(0.066)	
Conflict Dummy (3 months)	0.024		0.012		−0.089	
	(0.113)		(0.087)		(0.073)	
Disaster Dummy (1 year)		−0.046		−0.089*		0.020
		(0.066)		(0.045)		(0.040)
Conflict Dummy (1 year)		0.001		0.067		0.039
		(0.090)		(0.067)		(0.065)
Negative GDP Change Dummy (2011-2012)	0.003	0.006	−0.048	−0.042	−0.041	−0.039
	(0.072)	(0.071)	(0.047)	(0.046)	(0.044)	(0.044)
Age	−0.013	−0.013	−0.050	−0.048	0.230***	0.231***
	(0.036)	(0.036)	(0.034)	(0.034)	(0.035)	(0.035)
Married	0.032*	0.032*	−0.015	−0.015	0.034**	0.034*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Education Level	0.203***	0.202***	0.165***	0.163***	−0.002	−0.003
	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Female	0.044***	0.044***	0.077***	0.077***	0.031*	0.031*
	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.013)
Income Quantile	0.122***	0.121***	0.122***	0.121***	0.013	0.015
	(0.020)	(0.021)	(0.018)	(0.018)	(0.021)	(0.021)
Employed	0.054***	0.054***	0.042**	0.042**	0.017	0.017
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)
Village	0.030	0.029	0.007	0.009	0.007	0.008
	(0.030)	(0.030)	(0.025)	(0.025)	(0.026)	(0.025)
Suburb	0.010	0.010	−0.019	−0.017	−0.018	−0.018
	(0.043)	(0.043)	(0.034)	(0.035)	(0.038)	(0.038)
City	−0.010	−0.012	−0.014	−0.014	−0.018	−0.019
	(0.031)	(0.032)	(0.028)	(0.028)	(0.027)	(0.027)
Logged Population Total	0.216	0.226	−0.331	−0.253	−0.398	−0.339
	(0.269)	(0.272)	(0.265)	(0.240)	(0.254)	(0.241)
Logged Area (km2)	0.118	0.102	−0.026	−0.050	−0.313*	−0.304
	(0.166)	(0.170)	(0.135)	(0.135)	(0.156)	(0.156)
Income Index (HDI)	−0.039	−0.033	0.359*	0.383*	−0.269	−0.229
	(0.227)	(0.225)	(0.180)	(0.182)	(0.167)	(0.174)
Logged Disaster Count (9 year before treatments)	0.122	0.142	0.200*	0.244*	0.292***	0.255**
	(0.105)	(0.130)	(0.085)	(0.098)	(0.085)	(0.087)
Logged Conflict Count (9 year before treatments)	−0.170	−0.167	0.130	0.042	0.120	0.023
	(0.176)	(0.195)	(0.136)	(0.154)	(0.123)	(0.114)
Average GDP change (9 years before treatments)	−0.221	−0.225	−0.194	−0.197	0.072	0.078
	(0.207)	(0.208)	(0.175)	(0.175)	(0.192)	(0.194)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	64	64	64	64	64	64
Number of Regions	927	927	927	927	927	927
Observations	60,446	60,446	60,254	60,254	59,404	59,404
Adjusted R^2	0.146	0.146	0.129	0.130	0.081	0.081

Note: All models estimated w/OLS. All outcomes are standardized, all treatments are scaled as 0-1 or binary. Standard errors are clustered at ADM1 level. Survey weights are employed.

Table A3: Shock Exposure and Prosocial Behaviors

	Dependent Variable: Prosocial Behavior	
Disaster Dummy (3 months, 12m-15m)	−0.014	
	(0.037)	
Conflict Dummy (3 months, 12m-15m)	0.079	
	(0.066)	
Disaster Dummy (1 year, 12m-24m)		−0.020
		(0.027)
Conflict Dummy (1 year, 12m-24m)		0.009
		(0.052)
Negative GDP change in 2012	−0.088***	−0.088***
	(0.024)	(0.025)
Age	−0.053*	−0.054*
	(0.023)	(0.023)
Married	0.025**	0.025**
	(0.008)	(0.008)
Education Level	0.121***	0.120***
	(0.013)	(0.013)
Female	0.002	0.002
	(0.007)	(0.007)
Income Quantile	0.058***	0.058***
	(0.012)	(0.012)
Employed	0.100***	0.100***
	(0.009)	(0.009)
Village	0.017	0.016
	(0.017)	(0.017)
Suburb	0.020	0.019
	(0.019)	(0.020)
City	−0.004	−0.005
	(0.017)	(0.018)
Logged Population Total	−0.146	−0.165
	(0.094)	(0.100)
Logged Area (km2)	−0.074	−0.080
	(0.082)	(0.081)
Income Index (HDI)	0.135	0.135
	(0.109)	(0.109)
Logged Disaster Count (8 year before treatments)	−0.012	0.001
	(0.050)	(0.054)
Logged Conflict Count (8 year before treatments)	0.108	0.160
	(0.080)	(0.104)
Average GDP change (8 years before treatment)	−0.117	−0.120
	(0.116)	(0.119)
Country Fixed Effects	Yes	Yes
Clustered Std. Errors	Yes	Yes
Number of Countries	64	64
Number of Regions	927	927
Observations	60,517	60,517
Adjusted R^2	0.638	0.638
Note:		*p<0.05; **p<0.01; ***p<0.001

To better align our model with the prosocial behavior index, which references actions from the year prior to the interview, we made two key adjustments. First, we extended our conflict and disaster exposure windows from the original 3 and 12-month intervals to new 12-15 and 12-24 month periods before the interview date. This change ensures that our exposure measurements correspond to the timeframe referenced in the survey questions. Second, we modified our historical shock variable, which originally covered the period from 10 years to 1 year before the interview. The new variable now spans from 10 to 2 years prior to the interview, maintaining a clear separation between long-term historical effects and more recent exposures captured by our treatment variables. These adjustments improve the temporal consistency of our analysis and more accurately reflect the timing implicit in our survey data.

Table A4: Shock Exposure and Prosocial Outcomes

	Dependent Variables:					
	Positive Reciprocity		Altruism		Trust	
Disaster Dummy (3 months)	−0.112*		−0.161**		−0.093	
	(0.048)		(0.058)		(0.069)	
Conflict Dummy (3 months)		−0.041		−0.082		0.022
		(0.064)		(0.044)		(0.039)
Disaster Dummy (1 year)	0.015		−0.0002		−0.093	
	(0.111)		(0.087)		(0.075)	
Conflict Dummy (1 year)		−0.006		0.064		0.029
		(0.090)		(0.068)		(0.067)
Negative GDP change in 2012	0.015	0.019	−0.046	−0.039	−0.017	−0.015
	(0.071)	(0.070)	(0.046)	(0.045)	(0.043)	(0.043)
Age 25 or less	−0.008	−0.001	0.038*	0.048*	−0.037*	−0.037
	(0.018)	(0.021)	(0.017)	(0.019)	(0.017)	(0.020)
Married	0.024	0.025	−0.006	−0.006	0.046**	0.046**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Education Level	0.207***	0.206***	0.167***	0.165***	−0.030	−0.030
	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)
Female	0.043***	0.044***	0.079***	0.079***	0.027*	0.027*
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)
Income Quantile	0.121***	0.120***	0.121***	0.120***	0.019	0.021
	(0.020)	(0.020)	(0.018)	(0.018)	(0.021)	(0.021)
Employed	0.052***	0.052***	0.048***	0.048***	0.006	0.005
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
Village	0.030	0.029	0.008	0.009	0.006	0.007
	(0.030)	(0.030)	(0.025)	(0.025)	(0.026)	(0.025)
Suburb	0.010	0.011	−0.019	−0.016	−0.020	−0.020
	(0.043)	(0.043)	(0.034)	(0.035)	(0.038)	(0.038)
City	−0.011	−0.012	−0.013	−0.014	−0.018	−0.020
	(0.031)	(0.032)	(0.028)	(0.028)	(0.027)	(0.027)
Logged Population Total	0.217	0.228	−0.332	−0.252	−0.407	−0.347
	(0.269)	(0.272)	(0.265)	(0.239)	(0.254)	(0.241)
Logged Area (km2)	0.120	0.104	−0.025	−0.048	−0.305	−0.297
	(0.165)	(0.169)	(0.136)	(0.136)	(0.157)	(0.156)
Income Index (HDI)	−0.038	−0.031	0.360*	0.384*	−0.260	−0.220
	(0.227)	(0.225)	(0.180)	(0.181)	(0.167)	(0.174)
Logged Disaster Count (9 year before treatments)	0.122	0.142	0.200*	0.244*	0.296***	0.259**
	(0.105)	(0.130)	(0.085)	(0.098)	(0.085)	(0.088)
Logged Conflict Count (9 year before treatments)	−0.170	−0.167	0.131	0.042	0.118	0.022
	(0.176)	(0.195)	(0.135)	(0.153)	(0.123)	(0.114)
Average GDP changes (9 years before treatments)	−0.221	−0.225	−0.192	−0.196	0.069	0.075
	(0.207)	(0.208)	(0.174)	(0.175)	(0.192)	(0.195)
Disaster within 3 Months * Age 25 or less	0.024		0.008		0.050	
	(0.048)		(0.052)		(0.064)	
Battle within 3 Months * Age 25 or less	0.028		0.034		0.001	
	(0.050)		(0.037)		(0.047)	
Disaster within Year * Age 25 or less		−0.017		−0.024		−0.002
		(0.030)		(0.028)		(0.031)
Battle within Year * Age 25 or less		0.021		0.011		0.022
		(0.039)		(0.034)		(0.036)
Negative GDP change in 2012 * Age 25 or less	−0.044	−0.047	−0.007	−0.012	−0.087*	−0.085*
	(0.032)	(0.033)	(0.033)	(0.033)	(0.040)	(0.040)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Std. Errors	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	64	64	64	64	64	64
Number of Regions	927	927	927	927	927	927
Observations	60,446	60,446	60,254	60,254	59,404	59,404
Adjusted R^2	0.146	0.146	0.130	0.130	0.080	0.080
Note:						*p<0.05; **p<0.01; ***p<0.001

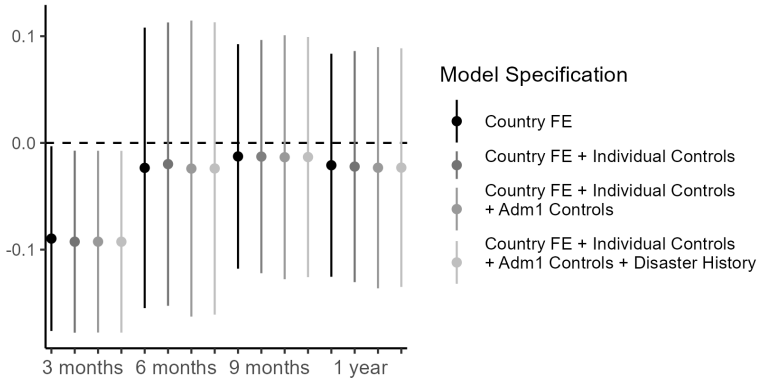
All models estimated w/OLS. All outcomes are standardized, all treatments are scaled as 0-1 or binary. Standard errors are clustered at ADM1 level. Survey weights are employed.

Table A5: Shock Exposure and Positive Reciprocity

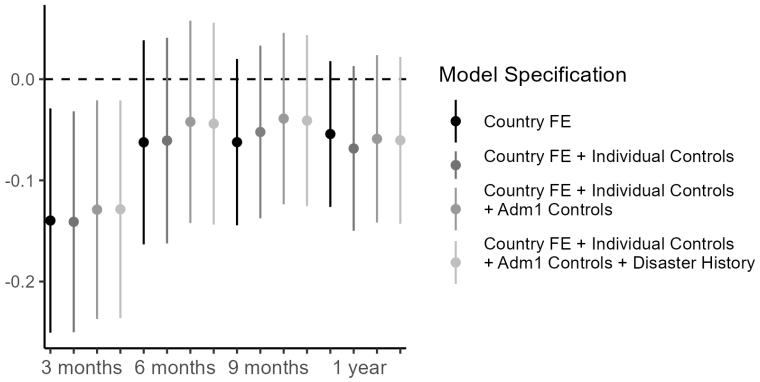
	Dependent Variable: Prosocial Behavior Index	
Disaster Dummy (3 months, 12m-15m)	0.013	
	(0.041)	
Conflict Dummy (3 months, 12m-15m)		−0.015
		(0.028)
Disaster Dummy (1 year, 12m-24m)	0.092	
	(0.069)	
Conflict Dummy (1 year, 12m-24m)		0.022
		(0.053)
Negative GDP change in 2012	−0.099***	−0.098***
	(0.024)	(0.024)
Age 25 or less	0.019	0.023
	(0.011)	(0.013)
Married	0.025**	0.025**
	(0.009)	(0.009)
Education Level	0.127***	0.126***
	(0.013)	(0.013)
Female	0.004	0.003
	(0.007)	(0.007)
Income Quantile	0.057***	0.057***
	(0.012)	(0.012)
Employed	0.103***	0.103***
	(0.009)	(0.009)
Village	0.017	0.016
	(0.017)	(0.017)
Suburb	0.021	0.020
	(0.019)	(0.020)
City	−0.004	−0.005
	(0.017)	(0.017)
Logged Population Total	−0.138	−0.162
	(0.094)	(0.100)
Logged Area (km2)	−0.076	−0.082
	(0.082)	(0.081)
Income Index (HDI)	0.137	0.133
	(0.108)	(0.109)
Logged Disaster Count (8 year before treatments)	−0.013	−0.001
	(0.050)	(0.054)
Logged Conflict Count (8 year before treatments)	0.109	0.160
	(0.080)	(0.104)
Average GDP changes (8 years before treatments)	−0.119	−0.121
	(0.115)	(0.119)
Disaster within 3 Months (12m-15m) * Age 25 or less	−0.100**	
	(0.039)	
Battle within 3 Months (12m-15m) * Age 25 or less	−0.038	
	(0.026)	
Disaster within Year (12m-24m) * Age 25 or less		−0.016
		(0.017)
Battle within Year (12m-24m) * Age 25 or less		−0.040
		(0.021)
Negative GDP change in 2012 * Age 25 or less	0.040*	0.034
	(0.020)	(0.020)
Country Fixed Effects	Yes	Yes
Clustered Std. Errors	Yes	Yes
Number of Countries	64	64
Number of Regions	927	927
Observations	60,517	60,517
Adjusted R^2	0.639	0.638
Note:		*p<0.05; **p<0.01; ***p<0.001

To better align our model with the prosocial behavior index, which references actions from the year prior to the interview, we made two key adjustments. First, we extended our conflict and disaster exposure windows from the original 3, 6, 9, and 12-month intervals to new 12-15 and 12-24 month periods before the interview date. This change ensures that our exposure measurements correspond to the timeframe referenced in the survey questions. Second, we modified our historical shock variable, which originally covered the period from 10 years to 1 year before the interview. The new variable now spans from 10 to 2 years prior to the interview, maintaining a clear separation between long-term historical effects and more recent exposures captured by our treatment variables. These adjustments improve the temporal consistency of our analysis and more accurately reflect the timing implicit in our survey data.

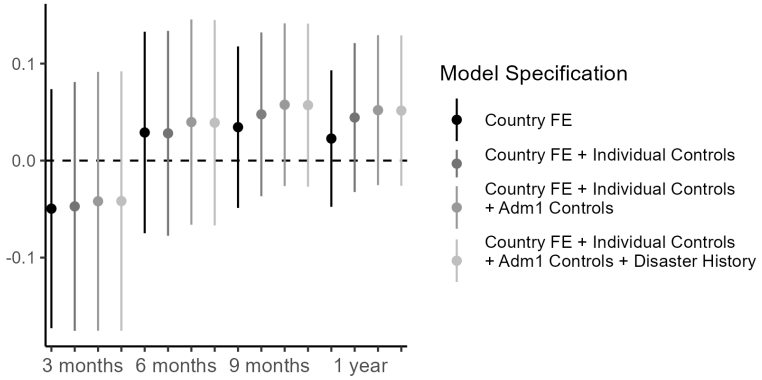
(a) Positive Reciprocity



(b) Altruism



(c) Trust



(d) Prosocial Behavior Index

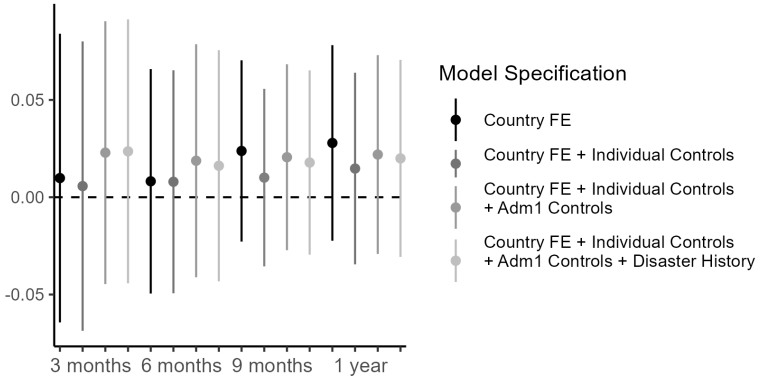
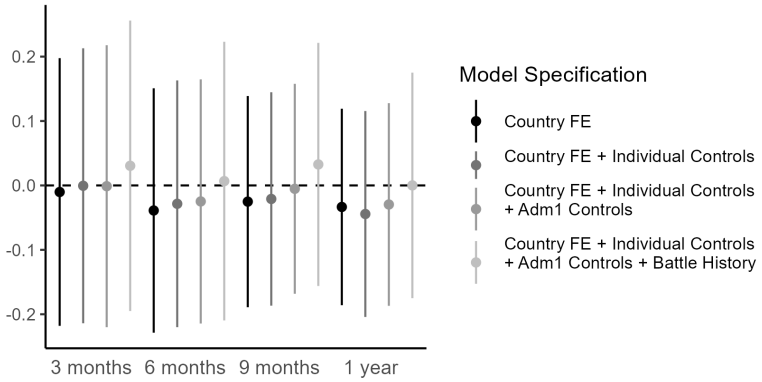
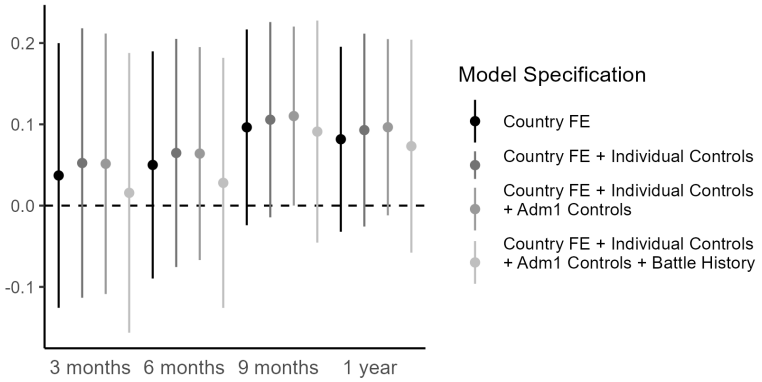


Figure A1: The Relationship between Natural Disasters and Social Preferences by Exposure Time and Specification. All models include ADM1-clustered standard errors.

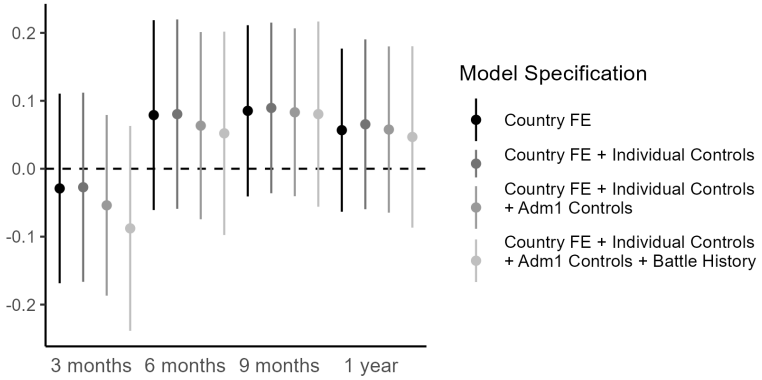
(a) Positive Reciprocity



(b) Altruism



(c) Trust



(d) Prosocial Behavior Index

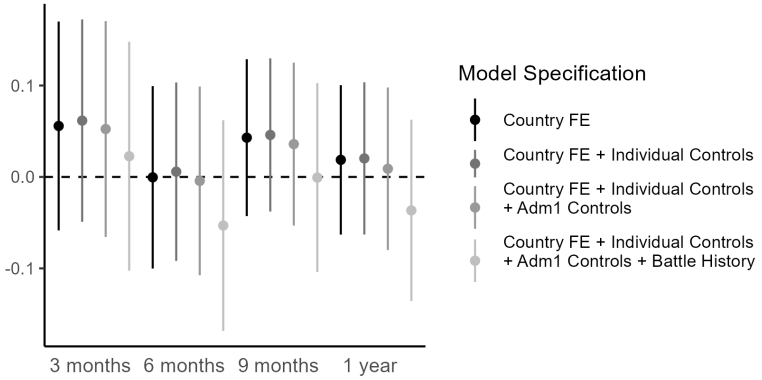
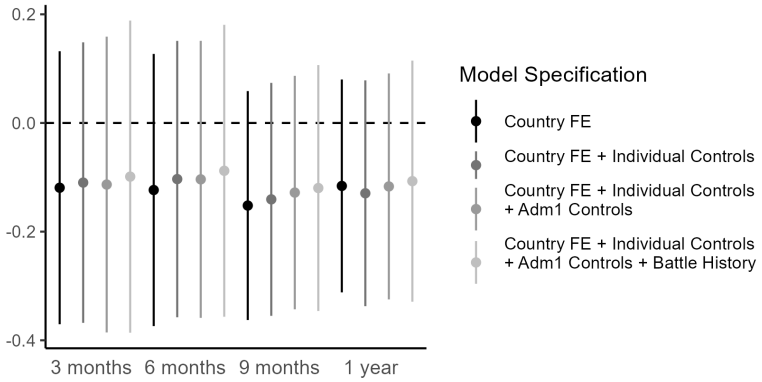
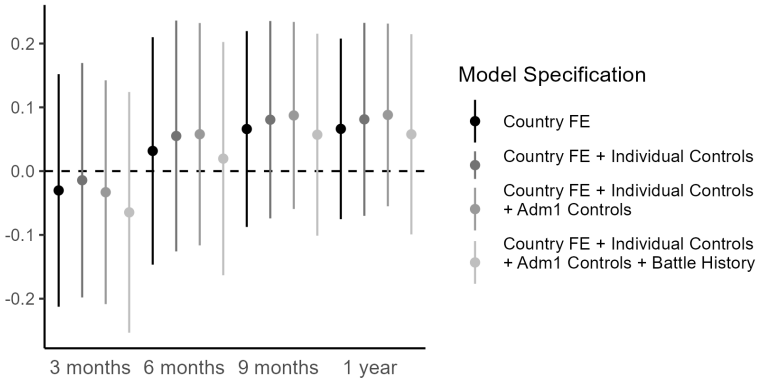


Figure A2: The Relationship between Conflicts and Social Preferences by Exposure Time and Specification. All models include Adm1-clustered standard errors.

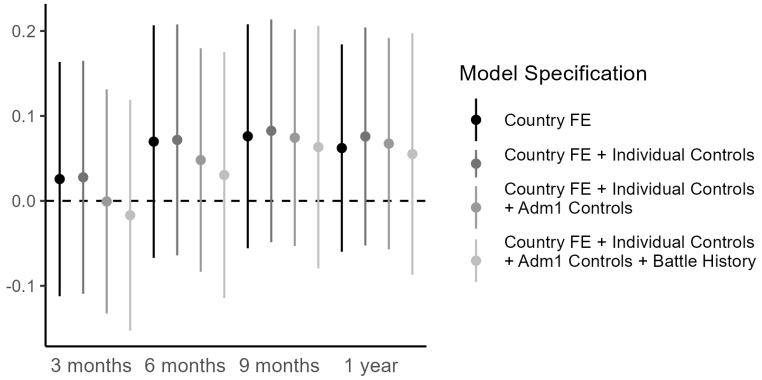
(a) Positive Reciprocity



(b) Altruism



(c) Trust



(d) Prosocial Behavior Index

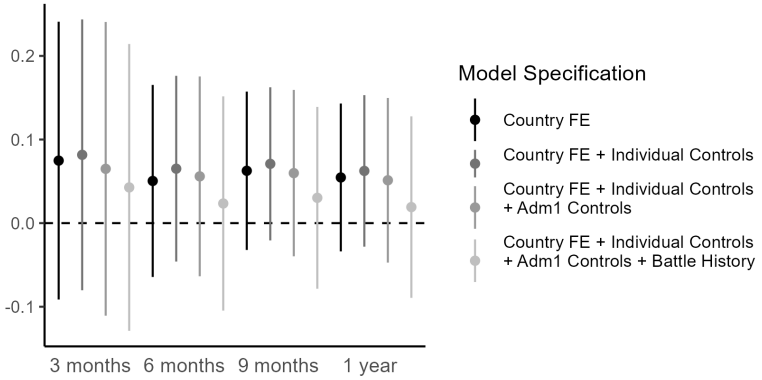
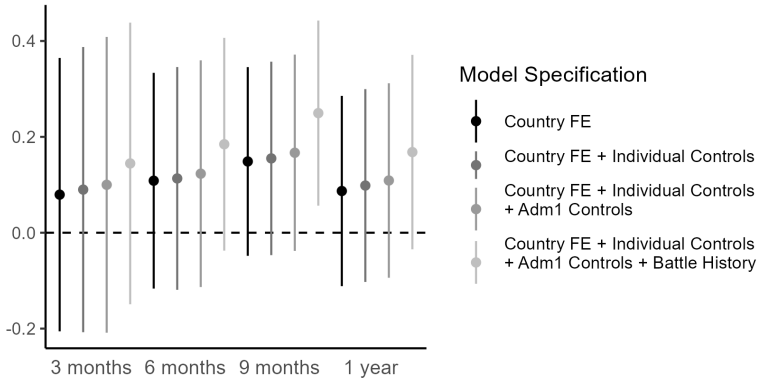
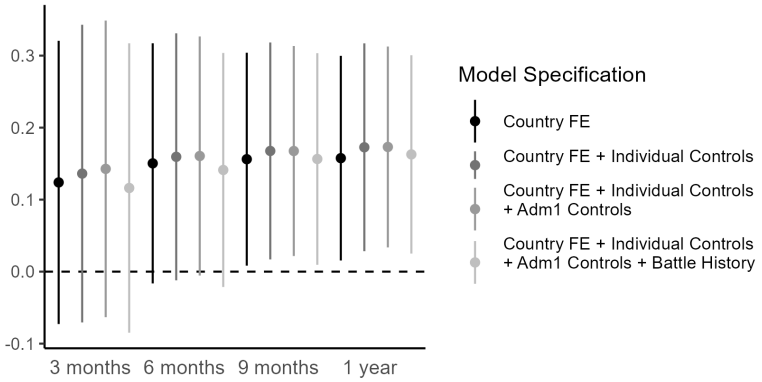


Figure A3: The Relationship between *State-based* Conflicts and Social Preferences by Exposure Time and Specification. All models include Adm1-clustered standard errors.

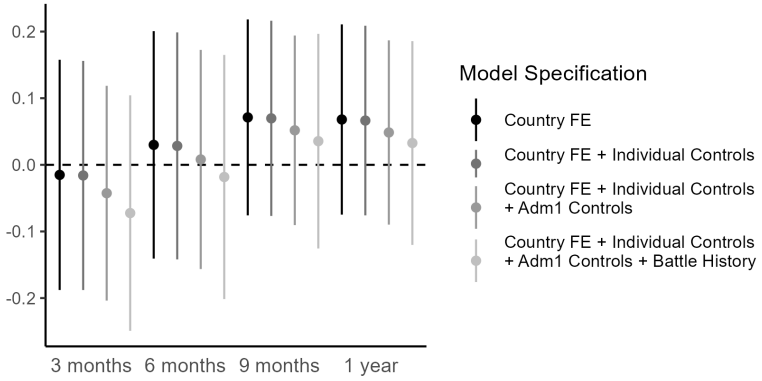
(a) Positive Reciprocity



(b) Altruism



(c) Trust



(d) Prosocial Behavior Index

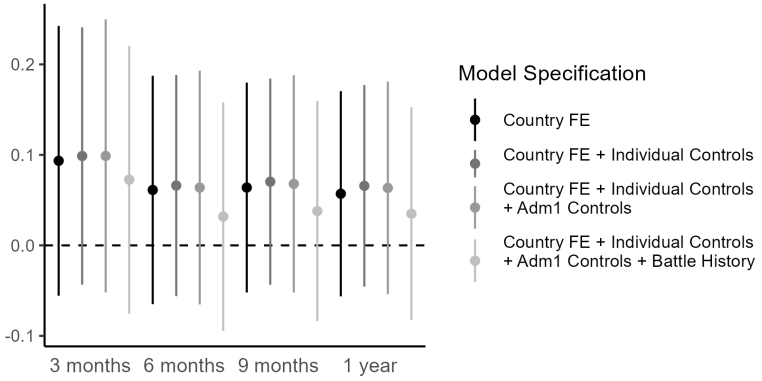
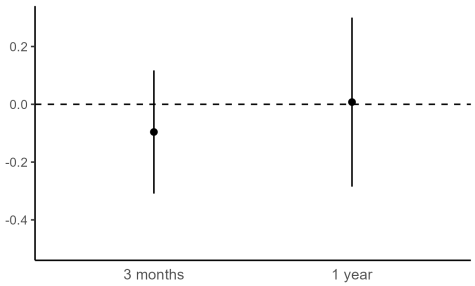
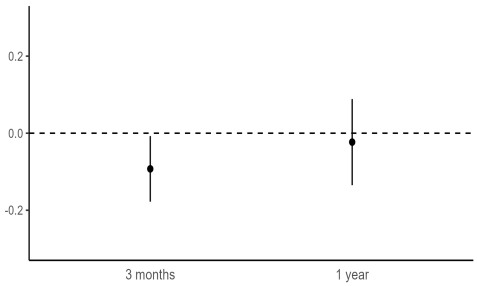


Figure A4: The Relationship between *One-sided* Conflicts and Social Preferences by Exposure Time and Specification. All models include ADM1-clustered standard errors.

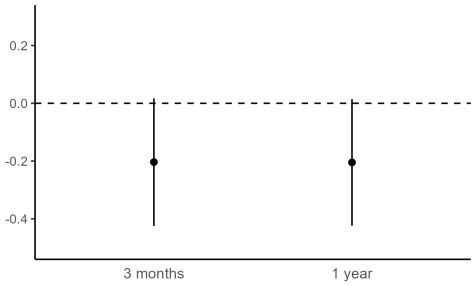
(a) Disaster Logged Count (0 to 1) and Positive Reciprocity (Z-scores)



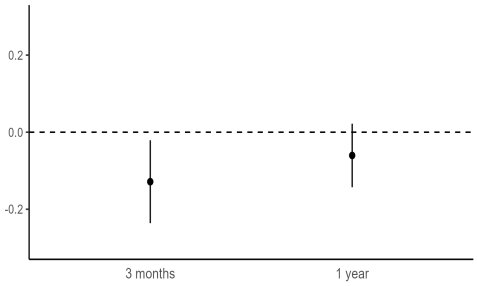
(b) Disaster Dummy and Positive Reciprocity (Z-scores)



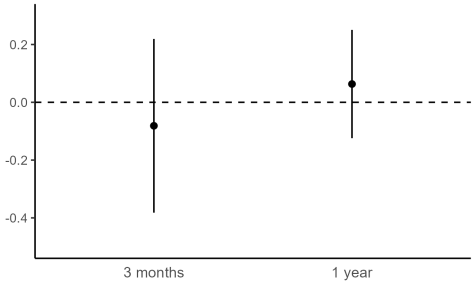
(c) Disaster Logged Count (0 to 1) and Altruism (Z-scores)



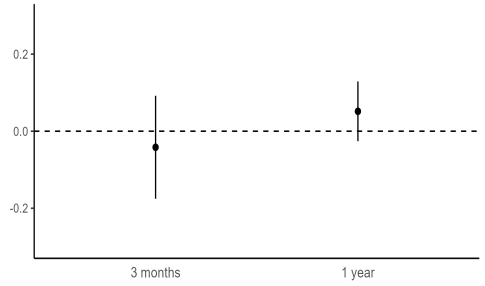
(d) Disaster Dummy and Altruism (Z-scores)



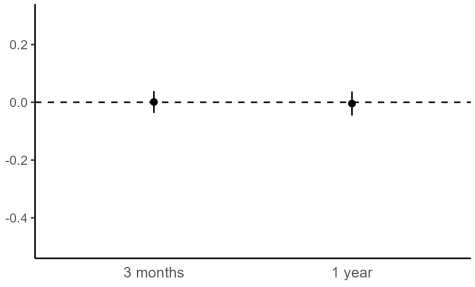
(e) Disaster Logged Count (0 to 1) and Trust (Z-scores)



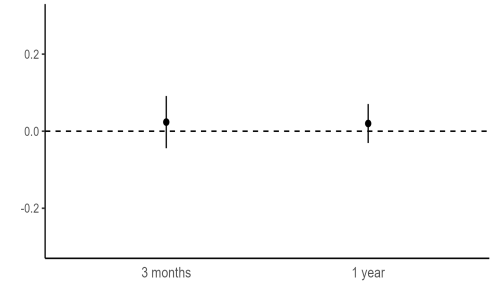
(f) Disaster Dummy and Trust (Z-scores)



(g) Disaster Logged Count (0 to 1) and Prosocial Behavior Index (Z-scores)



(h) Disaster Dummy and Prosocial Behavior Index (Z-scores)

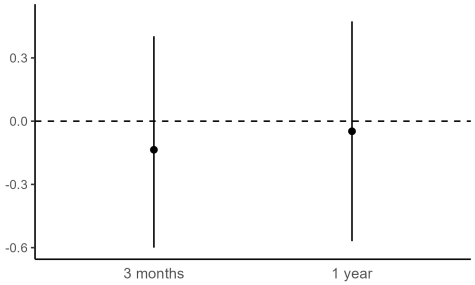


Model Specification (all): Disaster Count + Individual Controls + Adm1 Controls + Shock History

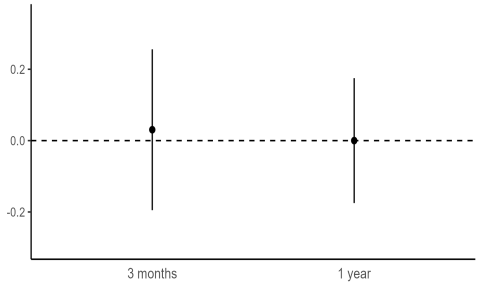
Model Specification (all): Disaster Dummy + Individual Controls + Adm1 Controls + Shock History

Figure A5: Figures illustrating the impact of natural disasters on prosocial outcomes. All models include Adm1-clustered standard errors.

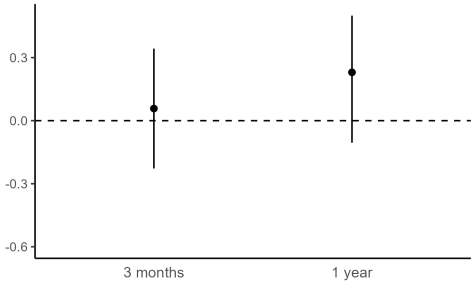
(a) Conflict Logged Count (0 to 1) and Positive Reciprocity (Z-scores)



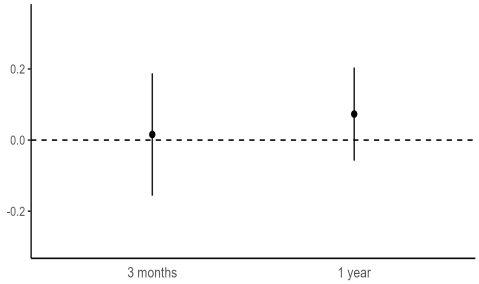
(b) Conflict Dummy and Positive Reciprocity (Z-scores)



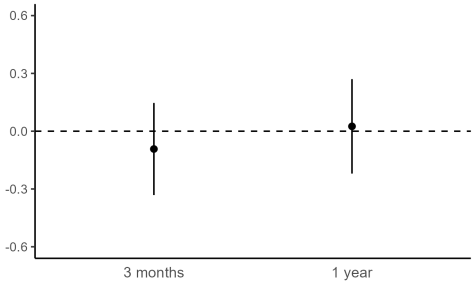
(c) Conflict Logged Count (0 to 1) and Altruism (Z-scores)



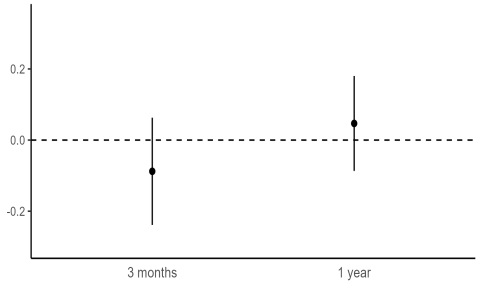
(d) Conflict Dummy and Altruism (Z-scores)



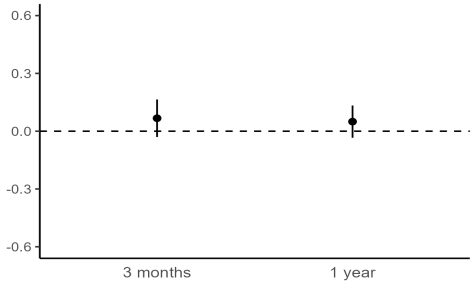
(e) Conflict Logged Count (0 to 1) and Trust (Z-scores)



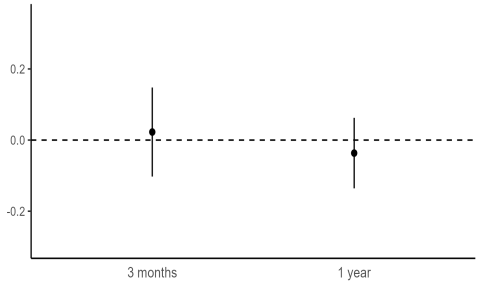
(f) Conflict Dummy and Trust (Z-scores)



(g) Conflict Logged Count (0 to 1) and Prosocial Behavior Index (Z-scores)



(h) Conflict Dummy and Prosocial Behavior Index (Z-scores)



Model Specification (all): Conflict Count + Individual Controls + Adm1 Controls + Shock History

Model Specification (all): Conflict Count + Individual Controls + Adm1 Controls + Shock History

Figure A6: Figures illustrating the impact of political violence on prosocial outcomes. All models include Adm1-clustered standard errors.

Table A6: Shock Exposure and Prosocial Outcomes

	Dependent Variables:							
	Positive Reciprocity		Altruism		Trust		Prosocial Behavior	
Logged Disaster Deaths (3 months)	−0.011		−0.378*		−0.155		−0.110	
	(0.160)		(0.164)		(0.159)		(0.090)	
Logged Disaster Deaths (1 year)		−0.090		−0.318		0.039		0.188
		(0.295)		(0.224)		(0.170)		(0.133)
Age	−0.012	−0.012	−0.051	−0.051	0.231***	0.231***	−0.054*	−0.054*
	(0.036)	(0.036)	(0.034)	(0.034)	(0.035)	(0.035)	(0.023)	(0.023)
Married	0.032*	0.032*	−0.015	−0.015	0.035**	0.035**	0.025**	0.025**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.008)	(0.008)
Education Level	0.203***	0.203***	0.164***	0.164***	−0.002	−0.003	0.121***	0.121***
	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.013)	(0.013)
Female	0.044***	0.044***	0.077***	0.077***	0.031*	0.031*	0.002	0.002
	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.013)	(0.007)	(0.007)
Income Quantile	0.031***	0.031***	0.031***	0.031***	0.003	0.003	0.015***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
Employed	0.053***	0.053***	0.041**	0.041**	0.017	0.017	0.099***	0.099***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.009)	(0.009)
Village	0.030	0.030	0.006	0.006	0.007	0.006	0.015	0.014
	(0.030)	(0.030)	(0.026)	(0.026)	(0.026)	(0.026)	0.018	0.018
Suburb	0.012	0.012	−0.018	−0.017	−0.021	−0.021	0.018	0.018
	(0.043)	(0.043)	(0.034)	(0.034)	(0.038)	(0.038)	(0.021)	(0.021)
City	−0.009	−0.010	−0.017	−0.018	−0.022	−0.022	−0.007	−0.006
	(0.031)	(0.031)	(0.028)	(0.028)	(0.027)	(0.027)	(0.018)	(0.018)
Logged Population Total	0.198	0.194	−0.315	−0.323	−0.350	−0.346	−0.129	−0.120
	(0.274)	(0.275)	(0.265)	(0.263)	(0.247)	(0.248)	(0.101)	(0.102)
Logged Area (km2)	0.079	0.078	−0.034	−0.037	−0.284	−0.284	−0.050	−0.049
	(0.167)	(0.167)	(0.132)	(0.132)	(0.158)	(0.158)	(0.089)	(0.090)
Income Index (HDI)	−0.098	−0.102	0.500	0.496	−0.407	−0.400	0.099	0.112
	(0.398)	(0.398)	(0.337)	(0.337)	(0.287)	(0.288)	(0.185)	(0.185)
Logged Disaster Count (9 year before treatments)	0.092	0.094	0.199*	0.199*	0.282***	0.278***	−0.013	−0.019
	(0.101)	(0.102)	(0.085)	(0.086)	(0.082)	(0.082)	(0.050)	(0.050)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	62	64	64	64	64	64	64	64
Number of Regions	927	1025	927	927	927	927	927	927
Observations	60,446	60,446	60,254	60,254	59,404	59,404	60,517	60,517
Adjusted R^2	0.145	0.145	0.129	0.129	0.081	0.081	0.637	0.637

Note: *p<0.05; **p<0.01; ***p<0.001

Table A7: Shock Exposure and Prosocial Outcomes

	Dependent Variables:							
	Positive Reciprocity		Altruism		Trust		Prosocial Behavior	
Logged Conflict Deaths (3 months)	−0.180		−0.248		−0.096		0.096	
	(0.273)		(0.214)		(0.192)		(0.136)	
Logged Conflict Deaths (1 year)		−0.349		−0.424		−0.136		0.082
		(0.328)		(0.229)		(0.206)		(0.150)
Age	−0.013	−0.013	−0.050	−0.050	0.233***	0.233***	−0.053*	−0.053*
	(0.036)	(0.036)	(0.034)	(0.034)	(0.035)	(0.035)	(0.023)	(0.023)
Married	0.032*	0.032*	−0.015	−0.015	0.035**	0.034**	0.025**	0.025**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.008)	(0.008)
Education Level	0.203***	0.203***	0.165***	0.166***	−0.001	−0.001	0.122***	0.121***
	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.013)	(0.013)
Female	0.044***	0.043***	0.076***	0.076***	0.031*	0.031*	0.002	0.002
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.007)	(0.007)
Income Quantile	0.123***	0.122***	0.122***	0.121***	0.013	0.013	0.060***	0.060***
	(0.020)	(0.021)	(0.019)	(0.019)	(0.021)	(0.021)	(0.012)	(0.012)
Employed	0.053***	0.053***	0.041**	0.041**	0.018	0.017	0.099***	0.099***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)	(0.009)	(0.009)
Village	0.030	0.029	0.006	0.006	0.007	0.007	0.015	0.015
	(0.030)	(0.030)	(0.026)	(0.026)	(0.026)	(0.026)	(0.018)	(0.018)
Suburb	0.014	0.014	−0.019	−0.019	−0.021	−0.021	0.016	0.016
	(0.043)	(0.043)	(0.034)	(0.035)	(0.037)	(0.037)	(0.021)	(0.021)
City	−0.009	−0.010	−0.016	−0.017	−0.020	−0.021	−0.007	−0.007
	(0.032)	(0.032)	(0.028)	(0.028)	(0.027)	(0.027)	(0.018)	(0.018)
Logged Population Total	0.234	0.215	−0.287	−0.310	−0.286	−0.292	−0.149	−0.146
	(0.263)	(0.269)	(0.258)	(0.253)	(0.251)	(0.250)	(0.093)	(0.094)
Logged Area (km2)	0.073	0.075	−0.051	−0.049	−0.310	−0.309	−0.051	−0.050
	(0.164)	(0.164)	(0.134)	(0.135)	(0.160)	(0.160)	(0.087)	(0.087)
Income Index (HDI)	−0.072	−0.074	0.324	0.321	−0.227	−0.228	0.078	0.078
	(0.238)	(0.237)	(0.195)	(0.194)	(0.173)	(0.173)	(0.111)	(0.110)
Logged Conflict Count (9 year before treatments)	−0.105	−0.066	0.196	0.240	0.104	0.117	0.143	0.139
	(0.176)	(0.188)	(0.128)	(0.135)	(0.118)	(0.124)	(0.084)	(0.090)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Countries	62	64	64	64	64	64	64	64
Number of Regions	927	1025	927	927	927	927	927	927
Observations	60,446	60,446	60,254	60,254	59,404	59,404	60,517	60,517
Adjusted R^2	0.145	0.146	0.128	0.128	0.079	0.079	0.638	0.638

Note: *p<0.05; **p<0.01; ***p<0.001

Data Sources

Individual-Level Survey Data

The individual-level data on social preferences and prosocial behaviors comes from the Gallup World Poll, an annually repeated cross-national survey conducted in over 160 countries. We use survey waves from 2012, focusing on variables capturing altruism, trust toward others, positive reciprocity, and other cooperative tendencies. Crucially, the Gallup data provides geographic identifiers down to the AdminLevel1 unit (states/provinces within countries), allowing us to geospatially match survey respondents to our data on conflicts and natural disasters.

Conflict Data

Information on armed conflicts is derived from the Georeferenced Event Dataset (GED) from the Uppsala Conflict Data Program. The GED codes the date, location, and event type for each individual incidence of organized violence. We distinguish violence directly targeting civilian populations from territorial battles involving state forces, coding separate variables for each (attacks on civilians and battles government battles). These variables are computed as dummies for 3-month, 6-month, 9-month, and 1-year windows preceding each respondent's interview date. To capture potential path dependencies, we also include a past exposure variable counting the total conflict events in the 9 years prior to the 1-year pre-interview window.

Natural Disaster Data

Data on natural disasters comes from the Emergency Events Database (EM-DAT) maintained by the Center for Research on the Epidemiology of Disasters. We code separate dummy variables for disasters with short and long onsets in the same temporal windows used for conflicts. The disaster and conflict variables are matched to the location and interview date of each Gallup respondent, allowing us to estimate impacts on prosocial preferences based on an individual's precise local exposure history. All variables are normalized to range from 0-1 prior to analysis.

Economic Downturns

Our measure of economic output shocks is derived from the income component of the Subnational Human Development Index (SHDI), which provides standardized measures of economic development across regions (Smits and Permanyer, 2019). We operationalize economic shocks by examining year-over-year changes in the income index at the subnational level, specifically focusing on the 2011-2012 period. Regions experiencing a negative GDP per capita growth rate between these years are classified as having undergone an economic downturn shock or a negative GDP shock, which we capture through a binary indicator variable.

Coding

All data processing and analysis was conducted using R statistical software. The Gallup World Poll microdata was imported into R using the haven package. The geographic identifiers were then standardized to follow the ISO codes for first level administration

units across all countries in the sample. For the EM-DAT natural disaster data and the GED conflict data, these datasets were directly loaded into R, with the geographic identifiers standardized to the same ISO first level administration units codes used in the Gallup data. The EM-DAT and GED datasets were then matched to the Gallup surveys based on the first level administration units geographic codes and the temporal windows around each respondent's interview date. This allowed creating the disaster duration, conflict type, and exposure history variables used in the regression models to estimate the impacts of the different types of shocks on prosocial preferences.

Coding Exceptions

The following cases were excluded from the analysis due to unclear assignment. These cases are idiosyncratically coded in the Gallup survey and include multiple first-level administrative units, grouped by regions:

Country	Region	Multiple units
Canada	Prairies	Yes
Canada	Atlantic	Yes
Ghana	Brong Ahafo	Yes
Japan	Kansai	Yes
Japan	Kanto	Yes
Japan	Kyushu	Yes
Japan	Shikoku	Yes
Japan	Hokuriku	Yes
Japan	Koshinetsu	Yes
Japan	Tohoku	Yes
Japan	Tokai	Yes
Japan	Chukyo	Yes
Japan	Chugoku	Yes
Kenya	Nairobi Area	Yes
Kenya	Central Province	Yes
Kenya	Coast Province	Yes
Kenya	Eastern Province	Yes
Kenya	Nyanza Province	Yes
Kenya	Rift Valley Province	Yes
Kenya	Western Province	Yes
Kenya	North Eastern Province	Yes
Hungary	Northern Great Plains	Yes
Hungary	Central Hungary	Yes
Hungary	Southern Great Plains	Yes
Hungary	Southern Transdanubia	Yes
Hungary	Central Transdanubia	Yes
Hungary	Northern Hungary	Yes
Hungary	West Transdanubia	Yes
Morocco	Meknes - Tafilalet	Yes
Serbia	South Serbia	Yes
Serbia	East Serbia	Yes
Serbia	West Serbia	Yes
Serbia	Central Serbia	Yes
Switzerland	Central Switzerland (CH06)	Yes
Switzerland	Eastern Switzerland (CH05)	Yes
Switzerland	Lake Geneva region (CH01)	Yes
Switzerland	Espace Mittelland (CH02)	Yes
Switzerland	Northwestern Switzerland (CH03)	Yes
Finland	West/Central Finland (Lansi-Suomi)	Yes
Finland	Southern Finland (Etela-Suomi)	Yes
Finland	Eastern Finland (Ita-Suomi)	Yes
Finland	Northern Finland (Pohjois-Suomi)	Yes
Peru	Selva (Forest)	Yes
Peru	Costa Norte (North Coast)	Yes
Peru	Sierra Norte (North Sierra/North Mountain)	Yes
Peru	Sierra Sur (South Sierra/South Mountain)	Yes
Peru	Sierra Centro (Central Sierra/Central Mountain)	Yes
Peru	Costa Sur (South Coast)	Yes
Peru	Costa Centro (Central Coast)	Yes
Phillipines	Balance Luzon	Yes
Phillipines	Visayas	Yes
Estonia	North-Eastern	Yes
Estonia	Central Estonia	Yes
Estonia	South Estonia	Yes
Estonia	West Estonia	Yes
Estonia	North Estonia	Yes
Portugal	Norte	Yes
Portugal	Centro	Yes
Portugal	Alentejo	Yes
Uganda	Central Region	Yes
Uganda	Eastern Region	Yes
Uganda	Northern Region	Yes
Uganda	Western Region	Yes
United Kingdom	Yorkshire and The Humber	Yes
United Kingdom	South West	Yes
United Kingdom	West Midlands	Yes
United Kingdom	North West	Yes
United Kingdom	East Midlands	Yes
United Kingdom	South East	Yes
United Kingdom	East of England	Yes
United Kingdom	North East	Yes
Sweden	Ostra Mellansverige	Yes
Sweden	Norra Mellansverige	Yes
Sweden	Vastverige	Yes
Sweden	Smaland med oarna	Yes
Sweden	Sydsverige	Yes
Sweden	Mellersta Norrland	Yes
Sweden	Ovre Norrland	Yes