School of Economics, Accounting and Finance

Social impacts of natural disasters in Africa

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i. Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Human Ethics: The research presented and reported in this thesis was conducted in accordance with the National Health and Medical Research Council National Statement on Ethical Conduct in Human Research (2007) – updated March 2014. The proposed research study received human research ethics approval from the Curtin University Human Research Ethics Committee (EC00262), Approval Number HRE2023-0368.

This research is supported by an Australian Government Research Training Program (RTP) Scholarship.

ii. Acknowledgement of Country

We acknowledge that Curtin University works across hundreds of traditional lands and custodial groups in Australia, and with First Nations people around the globe. We wish to pay our deepest respects to their ancestors and members of their communities, past, present, and to their emerging leaders. Our passion and commitment to work with all Australians and peoples from across the world, including our First Nations peoples are at the core of the work we do, reflective of our institutions' values and commitment to our role as leaders in the Reconciliation space in Australia.

iii. Abstract

Natural disasters are often discussed in terms of immediate costs and fatalities with relatively little said of the enduring social impacts. However, the underlying social structures and values in developing countries often contribute to the ability for these nations to pursue economic development. The aim of this thesis is to provide a multi-country individual-level analysis of the social consequences of disaster exposure, based on an empirical study of African countries, in the hope of better understanding disaster impacts and providing improved insights for future policy.

The thesis is comprised of three essays. Essay One explores how individuals cope when exposed to disaster and highlights the preferences for collective action under the deteriorating institutional circumstances in disaster-affected areas. Essay Two considers the impact of disaster exposure throughout an individual's impressionable years on generalised trust, documenting the long-lasting impact of disaster exposure on the formation of trust. Essay Three studies the effects of disaster exposure on the incidence of crime and explores the motivations underlying criminal behaviour in a post-disaster setting. The three essays use data from the Afrobarometer survey over the 1999 - 2016 period matched with geocoded data from the Global Disasters Dataset. In addition, Essay Three complements the quantitative methodology with primary data on crime scenarios collected from Kenya. The findings across the essays point to exacerbated vulnerabilities caused by natural disasters that create enduring social consequences for the communities.

iv. Acknowledgements

I would firstly like to extend my sincere thanks to my supervisors Professor Astghik Mavisakalyan, Dr. Yashar Tarverdi, and Dr. Jaslin Kalsi. Their patience with me whilst completing my PhD on the other side of Australia does not go unappreciated.

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Lastly, it is my sincere hope that this research contributes to course-correcting how we respond to our changing climate and disasters, the victims of which are often the most marginalised.

v. Attribution Statement

This thesis contains three co-authored papers that have been submitted for publication in peer-reviewed journals. I was principally responsible for the conceptualisation of the study, all data analyses, interpretation of results, and writing of the three papers, however my co-authors contributed significantly to the overall papers as they are now presented.

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1. Introduction

The number of natural disasters occurring globally continues to increase, threatening communities and their social fabrics. When considering the consequences of natural disasters, we too often think strictly of the loss of life or economic burden. Whilst these impacts carry more immediacy and provide crucial tools in measuring disaster severity, there are more long-term societal impacts that have an enduring effect on the communities' ability to develop and recover. Emerging and growing discourse on this subject suggests that behavioural and attitudinal changes arise as consequences of disasters (Islam and Nguyen, 2018; Rahman et al. 2020; Berrebi et al. 2021; Li et al. 2021; Gaherity and Birch, 2022).

Natural disasters are often the cause, or the exacerbator, of economic vulnerabilities for individuals and communities. The severity of those vulnerabilities is often dictated by the strength of the presiding social fabrics and pre-existing institutions. These detrimental effects are particularly felt by developing communities which are more susceptible to shocks (Cox & Perry, 2011; Bouchard et al., 2023). Additionally, disasters may also disrupt pro-social behaviours or alter individuals' perceptions of their community and their peers. Critical tenants of social cohesion such as trust are crucial for economic development and societal progression and the disruption of these tenants can be destructive (Arrow, 1972; Ward et al. 2014).

Economists have tried to understand what underpins behavioural change after a shock and what mechanisms influence these. Whether it be institutional stability, resource windfalls, underlying fractions in the community, the disaster response, or the severity of the disaster itself, seems contextual and situational to the disaster, the location, and the people (Arcenaux and Stein, 2006; Leeson and Sobel, 2008; Wirasinghe et al. 2013; Frailing et al. 2015; Uslaner, 2016; Kwanga et al., 2017; Nguyen, 2017). Additionally, whether the vulnerabilities found in developing communities compound the social consequences of disasters or influence the behavioural change is a growing topic – one in which this thesis contributes towards.

The study of natural disasters in Africa is still an emerging topic, with many developing-country studies focused on Asia and South America (Carlin et al. 2014; Calo-Blanco et al., 2017; Islam and

Nguyen, 2018; Purnama et al. 2020; Rahman et al. 2020; Li et al. 2021; Siddiqui, 2023). Africa falls victim to numerous events of disaster annually, the effects of which are worsened by growing populations, poverty, and poor institutional capacities (Khandlhela and May, 2006; Yameogo et al. 2018; Hallegatte et al. 2020). African nations already struggle to manage their arid landscape, and their economies are highly responsive to weather shocks. How these pre-existing and contextual traits affect communities responding to disaster is a topic not yet fully realised in the literature. This research gap raises questions in this unstable climate on *how do individuals exposed to disaster cope and respond*, and *what changes in behaviour are dictated by natural shocks*?

Contributions

This thesis comprises three essays that engage in a detailed empirical analysis of the social impacts associated with disaster exposure in developing countries across Africa. Using geo-coded individual level secondary survey data and geographic disaster data, the study examines how disaster exposure affects collective coping (the first essay), interpersonal trust (the second essay), and, with the addition of collected primary data, crime in Kenya (the third essay). These essays provide detailed and nuanced insights into the behavioural changes in developing communities when exposed to disaster with novel methodological contributions.

This thesis and the broader research surrounding it contributes to the literature in significant ways. There is a rich existing literature concerning the consequences of natural disasters on social and behavioural impacts (Castillo and Carter, 2011; Fleming et al., 2014; Albrecht, 2017; Calo-Blanco et al., 2017; Kwanga et al., 2017; Malesic, 2019; Rahman et al., 2020; Bai and Li, 2021; Berrebi et al. 2021; De Juan and Hanze, 2021; Lee, 2021; Wright and Stewart, 2024), however this thesis takes alternative approaches to the ideas of social impacts. The first essay studies the impact of natural disasters on collective coping – an outcome that is novel to the literature and offers emerging evidence on potentially causal social impacts of disasters, such as: disasters may result in higher engagement in collective action and may also lead to reduced political engagement.

The second essay studies the effects of compounded disaster exposure throughout the impressionable years (18 – 25) providing insights into how exposure to disasters may result in reduced interpersonal and institutional trust. In doing so, it adds to the emerging body of work on the impressionable years hypothesis. Many studies have shown economic, political, or health shocks (De Juan and Pierskalla, 2016; Roth and Wohlfart, 2018; Bai and Wu, 2020; Fang et al. 2023) during this period of a young adults life can alter behaviours and beliefs, however there had not been sufficient evidence concerning natural shocks. By compounding an individual's exposure to natural disaster throughout their impressionable years, this work adds notable understanding on natural shocks in the impressionable years and is the first to do so in the African context.

The third essay looks at the impact of natural disasters on crime, adding to the literature that has produced mixed findings on the relationship between disasters and crimes, as well as contributing detailed insights on transmission mechanisms. This essay finds disaster exposed individuals may have more frequent experiences with crime. The contributions of each essay provide valuable tools in policy planning and highlight several policy opportunities for mitigating the effects caused by disaster exposure.

The thesis additionally provides novel methodological contributions across each of the essays, expanding upon existing work or adding new insights to the literature. As existing disaster research has been done in the context of singular disaster events or at the level of countries, the detailed micro-level study used in this thesis addresses endogeneity issues and adds to the growing evidence on potentially causal impacts of disasters (Kayser et al., 2008; Chang, 2009; Dussaillant and Guzmán, 2014; Yamamura, 2014; Rahman et al., 2017; Gualtieri et al. 2019; Jovita et al. 2019; Rahman et al. 2020; Cisterna et al. 2022). Often the literature disregards that there may be systematic differences between individuals who reside closer to and further from disaster-prone areas. To address this identification challenge and expanding upon a set-up used by Knutsen et al. (2017) and Isaksson and Kotsadam (2018) this thesis contributes to the literature using a cross-sectional difference-in-differences model that ultimately compares individuals with disaster exposure with those at risk of exposure (residing in disaster prone areas, however not yet exposed). Moreover, the third essay combines the analysis of secondary quantitative data with primary qualitative data, thereby contributing rich and nuanced insights on the mechanisms mediating the impact of natural disasters – a novel approach to the literature.

Policy implications

This thesis presents significant insights for policy reforms concerning how individuals and societies respond to natural disasters, including how governing bodies may offset the social impacts caused by these shocks. The adverse impact on developing societies caused by disasters remains a matter of important policy relevance and this research provides some policy implications that could be utilised in disaster planning (IPCC, 2022). Understanding that individuals lean on their communities in response to a disaster is valuable for policy planning, since it suggests that utilising grassroots approach to recovery would likely gain traction and support. Additionally, the observed effects on social cohesion (reduced trust and increased incidence of crime) suggest the need for greater institutional response and/or presence in communities after disaster to offset the development of antisocial behaviours.

Lastly, many of the observed responses to disasters are not an isolated response to the shock, but to the lack of institutional reliability or pre-existing societal issues. This research, therefore, presents an additional and important opportunity to address foundational issues in institutional and ingrained societal issues that prevent or delay effective disaster recovery action.

The rest of this thesis proceeds as follows: chapter two studies collective coping after disaster exposure, chapter three explores the disruption of generalised trust with exposure to disaster in the impressionable years, and chapter four focuses on the increase in, and mechanisms driving, crime after disaster, whilst chapter five concludes.

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2. Coping collectively: Responses to natural disasters in Africa

This chapter has been presented at the 2024 Centre for the Study of African Economies conference, The University of Oxford (2024, Oxford, United Kingdom). Feedback and commentary have been included in this thesis.

This chapter has been made available as a working paper on SSRN (ID 4333165).

This chapter is currently under a review and resubmit at Energy Economics.

2.1. Introduction

The frequency of natural disasters has increased significantly over the past decades. Based on the Ecological Threat Report (2020), there has been a tenfold increase in the number of natural disasters between 1960 - 2019. The resulting adverse impacts on societies, which are particularly pronounced in developing country contexts, is a matter of significant policy relevance (IPCC, 2022). Natural disasters exacerbate vulnerabilities, increasing the demand for public services. Yet, in developing country contexts often characterised with deficient institutions, the capability to address such demand is at times extremely constrained. Moreover, natural disaster recovery and aid influx also create resource windfalls resulting in more rent-seeking behaviour and corruption in such contexts (e.g., Leeson and Sobel, 2008; Wenzel, 2021; Zafar et al. 2023), which, in turn, deteriorate the quality of publicly provided services and individuals' ability to afford and access these.

Such scenarios are increasingly common. For example, the 2023 earthquakes in Turkey and Syria, measured at magnitudes of 7.7 and 7.6, killed over 50,000 people, and destroyed many towns and cities in the two countries (Al Jazeera, 2023). While the need for recovery efforts under these circumstances has been immense, the governments in the two countries have not been well positioned to deal with the task. Both are characterised by poor institutions following the civil war brought on by Bashar al-Assad's dictatorial regime in Syria and the economic crisis under the authoritarian regime of Tayyip Erdogan in Turkey. Indeed, Turkey's government has been extensively criticised over the pace of its recovery efforts (Chotiner, 2023).

So how do individuals respond to the hardships under natural disasters in environments characterised by deficient institutions? Despite the gravity of the question, there is lack of systematic evidence on whether individuals exposed to natural disasters appear to cope collectively (as a group) or individually, especially in developing country contexts. To address this research gap, this paper explores the processes of collective coping drawing on data from over 175,000 individuals in 37 countries in Africa over the period from 2002 to 2015. Our analysis is based on matching geo-referenced individual-level data from the Afrobarometer social survey with data from the Geocoded Disasters Dataset (GDIS), which geographically pinpoints all global disasters recorded by the Emergency Events Database (EM-DAT) to a specific longitude and latitude, allowing us to assess the relationship between natural disaster occurrence and individual-level attitudes and behaviours at local level. From an econometric perspective, the results based on simply regressing the outcomes of our interest on disaster occurrence are likely to suffer from endogeneity bias since individuals who live close to disaster locations might be different from those who live further away in ways that correlate with social perceptions and behaviours. To address this possibility, we adopt a difference-in-differences strategy that exploits spatial and temporal distances to disaster events, drawing comparisons between individuals who were exposed to a disaster before (i.e., actually exposed) and after (i.e., at risk of exposure) the survey.

Our analysis confirms that natural disasters result in increases in the incidence of various hardships such as unemployment and going without food as a result of disaster exposure. We additionally highlight the institutional constraints faced by individuals in disaster-affected areas by showing that they exhibit an increased perception of government corruption and a greater dissatisfaction with government's performance. The core part of our analysis on collective coping responses demonstrates that individuals' response to disaster exposure is to become more collectively active with a greater likelihood of attending community meetings or getting together with others to raise an issue, and a higher propensity to contact their community or government leaders as part of a collective rather than individually. Disaster exposure is also associated with an increase in individuals' interest in public affairs and pro-democratic attitudes, however we do not observe a shift in political behaviours of individuals exposed to a disaster.

This study offers several distinct contributions to the literature. First, it extends the literature on the political economy consequences of disasters by offering a novel insight: that disasters may result in lower engagement with government and higher engagement in collective action. Unlike our micro-level work investigating the impact of over 1000 disasters on responses of over 175,000 individuals in 37 countries, existing work has documented correlations in the context of particular disasters e.g. the 2004 tsunami in Tamil Nadu, India (Kayser et al., 2008) or the 2005 flood in Carlisle, UK (Chang, 2009). Furthermore, most studies on the political economy impacts of disasters have been conducted at the level of countries, failing to convincingly address the issues of selection and endogeneity inherent to the relationship between disasters and social and political outcomes (e.g. Yamamura, 2014; Rahman et al., 2017). The limited micro-level literature has often achieved little progress in establishing close-to-causal estimates due to not accounting for the underlying differences in the characteristics of exposed vs. unexposed individuals (e.g. Wenzel, 2021; Khurana et al., 2022). An exception is the study by Chung and Rhee (2022) which uses a difference-in-differences approach based on spatial and temporal proximity to disaster occurrences to study their effects on individuals' perceptions of outgroups. By adopting a similar approach, we add to the emerging evidence on potentially causal social impacts of disasters.

Second, we extend the literature on the consequences of disasters in developing country contexts. This literature has considered the impacts of disasters on social capital and cohesion (Calo-Blanco et al., 2017; Bai and Li, 2021), political engagement (Fair et al., 2017), personal aspirations (Kosec and Mo, 2017), trust (Fleming et al., 2014; Rahman et al., 2020; Lee, 2021), and other cooperative traits (Castillo and Carter, 2011). In the context of Africa, studies have documented the impacts of disasters on intra-ethnic and inter-ethnic trust (De Juan and Hanze, 2021), agricultural production (Coulibaly et al., 2020), and out-group preferences (Chung and Rhee, 2022). Our focus on collective coping with the consequences of disasters brings novel insights to this literature.

Third, our work enriches the literature on coping in the face of disasters or other shocks which has produced several interesting and relevant insights. Bentzen (2019), for example, develops and tests a religious coping hypothesis: that individuals become more religious when hit by a natural disaster.

Studies on the political economy of the COVID-19 pandemic document significant decreases in voter turnout (Fernandez-Navia et al., 2021; Picchio and Santolini, 2022) and increases in the risk of conflict in places with weak government support (Ide, 2021; Farzanegan and Gholipour, 2023). In a study more closely related to ours, Hunt (2007) shows that victims of misfortune are more likely to increase their demand for public services and pay bribes. Our study, instead, provides evidence of disengagement with government and points towards an alternative coping mechanism: collective action.

The paper proceeds as follows: the next section discusses our key conjectures in more detail; section 3 describes our empirical strategy; section 4 presents our data and variables; section 5 presents the main results of our analysis while the associated robustness checks are presented in section 6; section 7 concludes the paper.

2.2. Background

2.2.1. Disasters and institutions

Disasters lead to economic vulnerabilities which, in turn, are likely to result in an increased demand for public services often provided by the government (Hunt, 2007; Peiffer and Rose, 2018). But how do natural disasters affect government performance?

According to a body of work, natural disasters create a climate that fosters corruption and poor governance outcomes. Disasters increase the incentives and opportunities of officials to successfully require bribes. They do so by creating resource windfalls through disaster relief from the central government or donor organisations which incentivise corruption (Leeson and Sobel, 2008; Yamamura, 2014). Nguyen (2017) also proposes that the collapse of infrastructure and the disorder resulting from natural disasters may worsen government transparency and facilitate corrupt behaviour. In addition, adverse events such as natural disasters increase the individuals' propensity to offer bribes to officials "possibly because victims are desperate, vulnerable, or demanding services particularly prone to corruption" (Hunt, 2007, p. 574). Consistent with these observations, several studies have found that natural disasters create opportunistic holes for corruption that could be mined by officials handling disaster response or leveraging the chaos to their advantage (Nguyen, 2017; Nikolova and Marinov, 2017; Wenzel, 2021).

More broadly, natural disasters may contribute to the environment that gives rise to autocratic institutions. For example, Rahman et al. (2017) suggests that repressive responses by the incumbent regime may arise as a response to violence, dissent, and plunder in the aftermath of a disaster or because an authoritative form of governance might be seen as more efficient at relief distribution. Rahman et al. (2022) present evidence consistent with these scenarios drawing on the case of island nations where autocratic tendencies in response to storm exposure are observed. Khurana et al. (2022) similarly discuss how disasters lead to a reduction in democratic accountability further affirming a habitat for corruption.

Individuals exposed to a disaster may shift their opinion on their institutions and leaders based on an increase in corruption and perceived decrease in performance. Arcenaux and Stein (2006) find that individuals in the United States may hold their governments responsible for the damage of a (unpredictable) disaster as they are perceived to be involved in the contingency planning and response designed to minimise disaster damage. Carlin et al. (2014) explore a similar line of governmental responsibility in Chile and find that exposure to disaster results in lower evaluations of institutions and a decreased legitimacy in local government.

In sum, based on existing studies, natural disasters are likely to result in negative perceptions and evaluations of government performance and have negative consequences for institutional quality. But if so, how do individuals and communities act to meet their needs considering poor government performance?

2.2.2. Coping responses to disasters

We consider two types of individual responses to the circumstances of economic vulnerability and poor-functioning governments in the aftermath of a disaster: first, individuals disenchanted with government may take control of action to improve their circumstances; and second, they may act together to remove the poor governing authorities from power.

In the context of disaster-caused damage, communities' cooperative capacity may become central to the generation of local public goods, especially in the presence of a poorly functioning and corrupt government. Local public goods may be provided through voluntary contributions of time, effort, and other resources by community members. While theoretical studies raise questions about achieving collective action (Hardin, 1968; Olson, 1965), empirical studies have provided insights on many successful cases of local collective action (e.g. Ostrom, 1990; Ostrom et al., 1994; Baland and Platteau, 1996; Shivakumar, 2005; Gellar, 2005).

Relevant to our study is the line of work that explores the relationship between government provision of, and voluntary contributions towards, public goods (Warr, 1982; Roberts, 1984; Bergstrom et al., 1986). The main finding of this literature is that government contributions to public goods should crowd out private contributions. On the other hand, as Casini et al., (2017) suggest, local collective action can influence the behaviour of government, leading to complementarities. However, assuming that government and private contributions are substitutes in the technology of providing public goods, as Casini et al. (2017) do, and given a deterioration in the quality of government service provision following a disaster, we should observe more incentives for collective provision of public goods. A line of empirical work lends support to this possibility by documenting an increase in local collective action following shocks such as conflict (Bellows and Miguel, 2006; 2009; Gilligan et al., 2013). In the context of natural disasters, Islam and Nguyen (2018) provide evidence from Cyclone Alia in Bangladesh of resource sharing within households' informal networks to assist in recovery. Similarly, a large body of work has highlighted the role of social organizations and collectivist context in post-disaster recovery (Kayser et al., 2008; Adviento and de Guzman, 2010; Kumar, 2017).

Another strand of theoretical literature suggests that poor government performance would incentivise voters to punish ineffective agents by removing them from office. Coined as 'democratic efficiency theory', this idea is associated with Wittman (1989; 1995) and has been tested in a number of studies. Leeson and Sobel (2011) find limited support for the theory in their study of mayoral elections in New Orleans following the 2005 Hurricane Katrina. Akarca and Tansel (2016) show that following the 1999 earthquake in Turkey, authorities were held accountable by the electorate. Rahman et al. (2017) shows that on one hand flooding induces the government to resort to autocratic behaviours, on the other hand, consistent with the democratic efficiency theory, it leads citizens to demand more democracy after experiencing corruption. Similarly, in a Chilean study, Carlin et al. (2014) find that whilst attitudes towards institutions had been compromised following disaster exposure, inclination towards political and social action had increased with a greater likelihood that individuals would become politically active or support a coup.

In contrast to the ‘democratic efficiency theory’, as Hermet (1978) and Karklins (1986) argue, if citizens view traditional political participation as legitimising their governments, disengagement may act as a similarly powerful political statement. Previous research in the case of some African countries has shown that in instances where an individual’s assessment of their political institutions has decreased, so too has their political engagement. Croke et al.’s (2016) research in Zimbabwe finds that non-participation in political platforms can be observed as a non-violent protest to delegitimise authorities and political regimes. Croke et al. (2016) and Dahlum and Wig (2019) each consider the influence of education on demonstrations and deliberate disengagement with government within the African context and find that a higher education often motivates disengagement. Similarly, Kolstad and Wiig (2019) find that when provided with more information about their political institutions (regarding tax havens and corruption) individuals in Tanzania were inclined to reduce their ‘faith in the social contract’ resulting in a diminished voter turnout and participation in political processes.

In a nutshell, individuals affected by a disaster in environments characterised by poor-quality institutions may engage in local collective action presumably with the objective of providing public goods in post-disaster recovery and/or they may engage in political action, presumably with the objective of removing the poorly functioning government from office (or they may disengage politically as an alternative form of expression of discontent with government). Our empirical work sheds light on these possibilities.

2.3. Empirical strategy

The goal of this paper is to determine how individuals' behaviours are shaped by their exposure to natural disasters. A key challenge in trying to establish this link is related to the fact that there might be systematic differences between individuals living close vs. further away to disaster locations. In particular, it may be certain type of individuals, predisposed to some of the behaviours we study in this paper, that are found in disaster-prone locations relative to others. Hence, a direct comparison of the behaviour of individuals living close to and far away from a disaster site is likely to affect the quality of inferences that can be drawn from the analysis.

To address this identification challenge, we adopt a spatial-temporal estimation strategy used by Knutsen et al. (2017) and Isaksson and Kotsadam (2018) in studies of causal effects of mining and foreign aid on corruption, and more recently adapted to the study of the causal effects of disasters on out-group preferences by Chung and Rhee (2022). This approach draws comparisons between individuals living near sites where a disaster took place before their survey interview and individuals living near sites where a disaster took place but only following their survey interview. This identification approach relies on knowing the locations and dates of both interviews and disaster occurrences to allow for the identification of individuals actually exposed to a disaster within a certain cut-off distance as well as those who we know would be exposed to a disaster but only after responding to survey questions.

The literature does not offer clear guidance on the choice of a cut-off distance for defining exposure to a disaster. For example, Belachsen et al. (2017) indicates that extreme rainfall events often show a high degree of spatial heterogeneity, suggesting it is difficult to pinpoint the location or scope of impact. In their study on the impact of natural disasters on out-group preferences, Chung and Rhee (2022) apply an arbitrary 50km cut-off to define exposure. On the other hand, the political economy studies of the local impacts of mining have used cut-offs ranging from 25km-50km (e.g. Knutsen et al., 2017; Isaksson and Kotsadam, 2018; Mavisakalyan and Minasyan, 2022). Given our focus on local impacts of natural disasters, we adopt a 30km spatial cut-off for defining disaster exposure in the baseline analysis, however, given that this choice is largely arbitrary, we conduct robustness checks allowing the cut-off to vary from 10km to 100km (at 10km intervals).

Like with spatial cut-offs, the literature does not offer clear guidance on temporal dimension of disaster exposure. Studies agree that the impact on individuals can be long term and that recovery for individuals and communities may not be linear (Green, 1995; Tierney and Oliver-Smith, 2012; Arcaya et al., 2020). Chung and Rhee (2022) allow for the impact of disasters to extend to an individual's entire lifetime; however, this leaves room for alternate exogenous variables to be influencing the individual's behaviour. We limit, again somewhat arbitrarily, the timeframe of disaster exposure to 15 years, but conduct robustness checks using alternate temporal cut-offs of both 5 and 10 years in our definitions of exposure. The use of 15-years temporal cut-off and the fact that the earliest survey date in our sample is 2002 mean that disaster records earlier than 1987 are not used in the analysis.

Based on the temporal proximity of a disaster to the respondent's interview date, we consider three groups: (a) individuals exposed to a disaster within 30km before interview, (b) individuals exposed to a disaster within 30km after interview, and (c) individuals not exposed to a disaster. Our regression model can be presented as follows:

$$Y_{ilt} = \alpha_1 exposed30\_before_{it} + \alpha_2 exposed30\_after_{it} + \boldsymbol{\gamma X'_{it}} + \delta_l + \theta_t + \varepsilon_{ilt} \qquad (1)$$

where the outcome of interest, Y, for an individual i residing in location l and interviewed in year t is assumed to depend on whether they have had, or could have had, exposure to disaster, $exposed30\_before_{it}$ or $exposed30\_after_{it,}$ together with a series of exogenous individual-level controls $\boldsymbol{X}_{it}$ including age, age-squared, gender and urban residence and dummies for sub-national region δ_l and year of interview θ_t.

Our analysis progresses in two stages. In the first stage, we establish the context of individuals hit by a disaster by documenting their economic vulnerabilities and the deficiencies of their institutional environment. In the second main stage, we consider their coping responses through community-focused and politically oriented actions. Accordingly, Y comprises a set of outcomes to capture individual-level economic vulnerabilities, perceptions of government performance and corruption, and collective coping responses. For ease of interpretation we estimate linear probability models, clustering the standard errors at the survey primary sampling unit (PSU) level.

As discussed earlier, interpreting the coefficient for before-the-survey exposure indicator (α_1) in isolation would give a biased evaluation on the true influence of disaster exposure. Inclusion of an indicator for after-the-survey exposure, $exposed30\_after_{it}$, ensures that comparisons are drawn between individuals already exposed to a disaster with individuals yet to be exposed to a disaster, and not just individuals exposed vs. not exposed to a disaster. Hence, we are interested in the differences in the parameters between $exposed30\_before_{it}$ or $exposed30\_after_{it,}$, α_1-α_2, and the associated test results. This approach effectively compares the difference between post-treatment individuals (exposed to a disaster within a 30km cut-off before the interview) and control individuals (not exposed to a disaster) with the difference between pre-treatment individuals (exposed to a disaster within a 30km cut-off after the interview) and control individuals (not exposed to a disaster) within the same region and year, providing a difference-in-difference estimator. In other words, the difference-in-differences approach compares the outcomes of individuals already exposed to a disaster with those yet-to-be-exposed to a disaster (see Knutsen et al., 2017 and Isaksson and Kotsadam, 2018 for further discussion of this approach).[1]

[1] Note that given the cross-sectional nature of our data, we cannot test for the parallel trends assumption of the difference-in-differences method, which remains a weakness of this study similar to those by Knutsen et al. 2017 and Isaksson and Kotsadam, 2018. Instead, we rely on the validity of a counterfactual, and as such, our strategy possesses traits of both a difference-in-differences and a natural experiment setting. In robustness checks, we enhance our natural experiment by dropping individuals who were never exposed to a disaster, thereby directly comparing the exposed before and after groups and testing the significance of the difference – see Appendix Tables A9 – A11.

2.4. Data

2.4.1. Sources

To estimate equation (1), we create a dataset geographically combining data on the precise timing and location of disasters with geo-referenced data on individuals in 37 African countries.

The source for disasters data is the Geocoded Disasters Dataset (GDIS), which provides information on the years, locations, and types of natural disasters between 1960 – 2018, including longitudinal and latitudinal spatial data (Rosvold & Buhaug, 2021). GDIS draws on the Emergency Events Database (EM-DAT), an international database that records disasters globally, and has been used in cross-country disaster literature concerned with impacts on outcomes such as economic development (Strömberg, 2007), civil conflict (Slettebak, 2012), the built environment (Rahman, 2018), and intergroup peace (Chung and Rhee, 2022). EM-DAT records a disaster based on whether at least one of the following criteria apply: whether 10 or more people have died, 100 or more people have been affected, a state of emergency has been declared, or there has been a call for international assistance (EM-DAT, 2022). Building on EM-DAT, GDIS makes it possible to study the impacts of natural disasters at a sub-national level.

GDIS contains spatial information on 39,953 locations for 9,924 unique disasters having occurred worldwide between 1960 - 2018 (some disasters have occurred in multiple locations, thus the variation in location to disaster ratio). Of these, 1,565 locations for 1,080 disasters are on the African continent. Not only does the source contain information on incidences and types of disasters, but also on fatality counts and dates of each disaster.

Due to the slow onset of droughts, EM-DAT records the start of a drought by the month of commencement. Studies approach the lack of the precise commencement date of a drought in the data by defining the start of a drought as when losses occur (Below et al., 2007) or by assigning the start date to the beginning of the recorded month (Rieckmann et al., 2018). Given that our identification approach, described in section 3, is reliant on the availability of the exact start dates of disasters, we exclude droughts from the analysis to avoid measurement error. Our baseline sample includes floods

(82,905 observations), storms (15,092 observations), and other grouped disasters (extreme temperature events, mass movement (dry) landslide, volcanic activity, and wildfire – an additional 1,081 observations).

Our individual-level data comes from the Afrobarometer, a collection of nationally representative repeated cross-sectional surveys conducted in up to 39 countries in Africa since 1999. The surveys contain rich data on a variety of opinions, priorities, preferences, and experiences alongside standard socio-economic and demographic characteristics of individuals (Afrobarometer Data, 2023). Moreover, the source contains a large set of questions pertaining to the outcomes of interest in the current study and has been used in previous work concerned with disadvantage and institutional quality in African countries (e.g. Knutsen et al. 2017; Isaksson and Kotsadam, 2018; Peiffer and Rose, 2018; Konte and Vincent, 2021). Our analysis employs data from rounds 2-6 (2002-2015) of the Afrobarometer survey conducted in 37 African countries.[2] The sub-nationally geo-coded version of the Afrobarometer rounds used in our study provides information on over 175,000 individuals in over 13,000 localities, including the longitude and latitude information (BenYishay et al. 2017).

2.4.2. Linking disasters to individuals

To study how disasters shape the outcomes of individuals, we link the data on disasters in GDIS to individual-level data in the Afrobarometer. We capture the incidence of living within a specific proximity of a disaster location, distinguishing between locations where a disaster occurred prior to the Afrobarometer survey, and ones where a disaster took place only after the survey.

Given our focus on local collective behaviours, as discussed earlier, our baseline approach employs a 30km radius spatial cut-off from the individuals' interview location. We measure the distance of disasters from the individual's PSU location and register if at least one disaster has occurred within

[2] Whilst Round 7 was available prior to this paper being drafted, we did not include it in the analysis as the geographic granularity of the geocoding compared to that found in Rounds 2 – 6 was inconsistent. Round 1 is not included in our research as specific dates of interviews were not available.

the 30km radius of the individual. An example can be seen in the Appendix Figure A1, which shows a 30km radius surrounding the PSU of Adjarra, Benin and the instances of disaster (orange squares) that occurred within that radius.

As discussed earlier, our baseline approach employs a 15-year temporal cut-off to measure exposure. We take the earliest record of a disaster that occurred within the 30km spatial cut-off in the 15 years either before or after the Afrobarometer interview date and subtract the interview date to determine whether an exposure occurred before or after the interview. Based on these proximities, we categorise individuals into one of the three groups: exposed before the interview; exposed after the interview; or not exposed (including individuals in PSUs where a disaster might have happened beyond the 30km spatial cut-off).

The GDIS data allows us to match data on 185,287 individuals including 79,690 individuals with an instance of disaster within the 30km cut-off.[3] Of these individuals, 54,568 were exposed to a disaster before interview and 25,122 were exposed after interview. The remaining 105,597 individuals of the reference group were not exposed to a disaster within 30km of their location.[4] Using the merged GDIS and Afrobarometer data, Figure 1 provides a map showing the distribution of individuals exposed to a disaster either before or after interview, with green circles indicating individuals who were exposed before their interview and red circles indicating those that were exposed afterwards. The size of the circle represents the number of individuals exposed in that PSU.

2.4.3. Variables

The definitions of our main dependent variables are presented in Appendix Table A2 while the sample means are reported in the regression tables.[5] As noted earlier, the focus of the first stage of our analysis

[3] Appendix Table A1 provides a breakdown of sample sizes per country and round of interview.

[4] The distribution of individuals across the three groups varies slightly across the sample sizes employed in different parts of the analysis.

[5] Some variables were exclusively from round 6 and these are indicated in the relevant models.

is to establish the context of individuals exposed to a disaster. We do so by documenting their economic vulnerabilities and the deficiencies of their institutional environment.

To study economic vulnerabilities, we look at individuals' assessments of the state of their living conditions, but we also look at their access to employment and food drawing on the literature that highlights the indirect economic impacts of disasters through product and factor markets (Okuyama and Sahin, 2009; Thomas et al. 2010). In our sample, around 48 per cent of individuals describe their living conditions as fairly or very bad (Table 1). Furthermore, 64 per cent of individuals do not have a job and 49 per cent report going without food. Finally, 16 per cent identify food shortage as one of the top three problems in their country.

Our study on the quality of institutions focuses on two aspects of institutional performance. First, we consider evaluations of government performance, including the performance of the local government and the member of parliament (MP), management of the economy overall as well as the perceived difficulty in accessing government-provided services. In our sample, 46 per cent of individuals disapprove of their local government's performance, whilst 48 per cent disapprove of their MP's performance (Table 2, Panel A). Additionally, 11 per cent of individuals identify the management of economy as one of the top three problems in their country, and 86 per cent report difficulty in accessing services in the past 12 months.

Second, we consider individuals' perceptions of corruption in government, among the MPs, within the police, whether they think corruption has increased and if it's among the top three priorities facing the country. In our sample, 62 per cent of individuals believe corruption has increased in the past year, whilst 89 per cent, 86 per cent and 90 per cent believe that at least some of their government officials, MP's and police force are involved in corruption respectively (Table 2, Panel B). However, only 10 per cent of individuals report corruption to be one of the top three problems in their country.

Figure 1. Distribution of Afrobarometer respondents by disaster exposure status

Note: Green circles indicate exposure to disaster before the interview and red circles indicate exposure after the interview. The size of the circle indicates the number of people exposed from each PSU.

Source: authors' creation using Afrobarometer and GDIS data. The map was created using Microsoft Excel.

To study the collective coping behaviours in individuals – the focus of the second and central part of the analysis - we mimic the literature and utilise information on the incidence of contacting government leaders and doing so individually or as a group, participating in the community through attending community meetings or getting together with others to raise an issue, and membership in voluntary associations or community groups (Kayser et al. 2008; Adviento and de Guzman, 2010; Yamamura, 2014; Kumar, 2017; Bai and Li, 2021). Of the individuals in our sample, only 25 per cent report contacting their local government councillor in the past year, and 12 per cent report contacting their MP in the past year (Table 3, Panel A). Where contact was made, 58 per cent report contacting as part of a group. Furthermore, 65 per cent of individuals report either attending a community meeting or raising an issue in the past year, while 23 per cent report having a group membership.

We also look at individuals' interest in public affairs and their views on appropriate behaviour of citizens in a democracy. Moreover, like studies on similar topics, we consider a range of politically oriented behaviours including attending a protest (Carlin et al. 2013), voting and being a member of a political party (Fair et al. 2017). In our sample, 56 per cent of individuals express an interest in public affairs and 29 per cent believe good democratic citizens can criticise government. Regarding political behaviours, 94 per cent of individuals were registered to vote, and 61 per cent were affiliated with a political party, however only 11 per cent of individuals had attended a protest or demonstration in the past year.

As discussed earlier; to study the consequences of exposure to disasters, we employ a difference-in-differences strategy that exploits spatial and temporal distances to disaster events. This approach is based on employing a set of three indicators. The indicator variable *exposed30_before* captures whether at least one disaster occurred within 30km of the individual throughout the 15 years before interview. The indicator *exposed30_after* captures individuals who were exposed to at least one disaster after their interview date. All other individuals are coded as not exposed. The share of *exposed30_before* individuals across the samples employed in the analysis is around 30 per cent, whereas the share of *exposed30_after* is around 14 per cent. The precise sample means of *exposed30_before* and *exposed30_after* variables are reported in all baseline regression tables.

2.5. Baseline results

2.5.1. Post-disaster context: economic vulnerabilities and institutional deficiencies

As noted earlier, our analysis starts with documenting the context of individuals following a natural disaster, providing evidence on the extent of their economic vulnerabilities and deficiencies of their institutional environment. The results of estimating equation (1) for the two sets of outcomes of interest are presented in Tables 1 and 2. We start by looking at the link between disaster exposure and levels of economic vulnerability in Table 1. As discussed in section 3, our focus here is on the difference-in-differences estimator and the associated test results.

The results suggest that individuals who have been exposed to a disaster are 2.6 percentage points more likely to report bad living conditions than individuals who are yet to be exposed to a disaster (model 1). They are also 2.4 percentage points more likely to not be employed (model 2). Our difference-in-differences estimates are also significant when looking at *Going without food* (model 3), *Frequency without food* (model 4) and *Food shortage a problem* (model 5) respectively as outcomes. Individuals exposed to a disaster are 1.6 percentage points more likely to report going without food and 3.4 percentage points more likely to go without food more frequently than average, relative to individuals yet to be exposed to a disaster. Compared to the same group, they are also 2.2 percentage points more likely to identify food shortage as a problem in their country.

Overall, these results confirm that disaster exposure increases economic vulnerabilities. Moreover, it should be noted that relative to non-exposed individuals, both *exposed_before and exposed_after* individuals appear to be less economically vulnerable (perhaps owing to the distinct features of their locations) as evident from the estimated negative coefficients on these individual terms in most models. This reinforces the point that individuals based in disaster-prone areas may be fundamentally different to those in other areas, which motivates the choice of the empirical strategy adopted in this paper.

We turn to the analysis of the link between disaster exposure and perceptions of quality of governance in Table 2. First, we consider individual assessments of the performance of institutions and leaders (Panel A). Relative to individuals yet-to-be exposed to a disaster, those exposed are 2.2 percentage points more likely to express a disapproval of local government performance and 3.4 percentage points more likely to express a disapproval of the performance of their MPs (models 1 and 2). Exposed individuals are also 1.9 percentage points more likely to identify the *Management of economy a problem* (model 3) in their country relative to individuals yet to be exposed to a disaster.

Lastly, disaster-exposed individuals are 2.9 percentage points more likely to experience *Difficulty accessing services* (model 4) relative to pre-treatment group.

Next, we turn to the analysis of the link between disaster exposure and perceptions of the prevalence of corruption in government bodies, as another dimension of quality of governance (Panel B of Table 2). The results point towards higher perceptions of institutional corruption among individuals exposed to a disaster relative to individuals yet-to-be exposed. The results of model (5) indicate that relative to yet-to-be exposed individuals, actually exposed individuals have a 3.5 percentage point higher probability of reporting an increase in the level of corruption. They are also more likely to hold the view that at least some government officials (model 6) and police (model 8) are involved in corruption. The difference-in-differences estimate for models 7 and 9 looking at corruption of MPs and whether individuals are more likely to see corruption amongst the top 3 problems facing their country, while positive, are insignificant.

Table 1. Disaster exposure and economic vulnerability: Baseline models

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Dependent variables	*Bad living conditions*	*Not employed*	*Going without food*	*Frequency without food*	*Food shortage a problem*
exposed30_before	-0.004	-0.006	-0.010*	0.007	0.008*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.004)
exposed30_after	-0.030***	-0.030***	-0.026***	-0.028*	-0.014**
	(0.009)	(0.008)	(0.008)	(0.014)	(0.006)
Difference in Differences	0.026	0.024	0.016	0.034	0.022
F-test: exposed30_before – exposed30_after = 0	8.404	8.209	3.754	5.263	10.991
P-value	0.004	0.004	0.053	0.022	0.001
Mean of dep variable	0.476	0.635	0.493	0.568	0.180
Mean of exposed30_before	0.303	0.304	0.304	0.314	0.303
Mean of exposed30_after	0.112	0.112	0.112	0.057	0.112
Sample size	157,516	157,720	158,034	52,277	158,344
R-squared	0.109	0.172	0.142	0.229	0.171

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference in differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age2, gender and urban dummy), region and year fixed effects. The full set of results including the estimated coefficients for main control variables are reported in Appendix Table A12. The definitions of dependent variables are provided in Appendix Table A2. The sample includes Afrobarometer rounds 2 – 6, except model (4) since the variable *Frequency without food* is available in round 6 only.

The findings in Table 2 provide strong empirical evidence that exposure to disaster has negative consequences for institutional quality, resulting in reduced evaluations of government performance and capability, and increased perceptions of institutional corruption.

2.5.2. Collective coping responses to disasters: community-focused and politically oriented actions

In Table 3 we turn to the analysis of individuals' coping strategies in response to disasters. As discussed, one potential response of individuals affected by a disaster may be to engage in local collective action. Panel A reports the analysis on the link between disaster exposure and community focused engagements. Firstly, we assess whether individuals exposed to a disaster are more likely to contact government representatives (models 1 and 2), and when they do that, if they are likely to do so as a group vs. individually (model 3). In line with the findings from Table 2 that suggest a reduced perception of institutional quality among disaster-exposed individuals, Panel A of Table 3 shows that individuals exposed to a disaster are 1.5 percentage points less likely to *Contact: Loc Gov* (model 1) relative to individuals who are yet to be exposed to a disaster. Whilst the difference-in-differences estimator for *Contact: MP* (model 2) is not significant, its negative sign supports the previous finding.

Furthermore, the results of model 3 show that relative to individuals yet-to-be exposed to a disaster, disaster-exposed individuals are 3 percentage points more likely to contact their government or community leaders as a group rather than individually – a finding that points towards the rise of local collective initiatives in disaster-affected areas. Similarly, the results of model 4, show that individuals exposed to a disaster are 2.5 percentage points more likely to have attended a community meeting or gathered to raise an issue in the last year, relative to individuals who were yet to be exposed to a disaster at the time of the interview. We do not, however, find statistically significant association between disaster exposure and formal membership of voluntary associations of groups.

Table 2. Disaster exposure and quality of governance: Baseline models

Panel A: Government performance				
	(1)	*(2)*	*(3)*	*(4)*
Dependent variables	*Disapproval of performance: Loc Gov*	*Disapproval of performance: MP*	*Management of economy a problem*	*Difficulty accessing services*
exposed30_before	-0.002	0.012**	0.008**	0.005
	(0.005)	(0.006)	(0.003)	(0.004)
exposed30_after	-0.024***	-0.022***	-0.012***	-0.024***
	(0.008)	(0.008)	(0.004)	(0.006)
Difference in Differences	0.022	0.034	0.019	0.029
F-test: exposed30_before – exposed30_after = 0	6.878	15.162	16.266	19.249
P-value	0.009	0.001	0.001	0.001
Mean of dep variable	0.457	0.480	0.133	0.849
Mean of exposed30_before	0.300	0.305	0.303	0.301
Mean of exposed30_after	0.115	0.111	0.112	0.104
Sample size	132,267	136,891	158,344	107,429
R-squared	0.097	0.102	0.079	0.085

Panel B: Perceptions of corruption					
	(5)	*(6)*	*(7)*	*(8)*	*(9)*
Dependent variables	*Increase in corruption*	*Corruption: Gov Official*	*Corruption: MP*	*Corruption: Police*	*Corruption a problem*
exposed30_before	0.008	0.005*	0.008**	0.005**	0.005**
	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
exposed30_after	-0.027**	-0.006	-0.002	-0.004	-0.001
	(0.013)	(0.005)	(0.005)	(0.004)	(0.004)
Difference in Differences	0.035	0.011	0.009	0.009	0.007
F-test: exposed30_before – exposed30_after = 0	6.104	4.531	2.586	4.152	2.413
P-value	0.014	0.033	0.108	0.042	0.120
Mean of dep variable	0.620	0.895	0.860	0.903	0.114
Mean of exposed30_before	0.314	0.308	0.311	0.308	0.303

Mean of exposed30_after	0.055	0.100	0.100	0.102	0.112
Sample size	49,711	136,771	131,649	142,367	158,344
R-squared	0.161	0.086	0.104	0.082	0.070

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The full set of results including the estimated coefficients for main control variables are reported in Appendix Table A13. The definitions of dependent variables are provided in Appendix Table A2. The sample includes Afrobarometer rounds 2 – 6, except Panel A model (4) as the variable *Difficulty accessing services* is not available in round 4, Panel B model (5) since the variable *Increase in corruption* is available in round 6 only, and Panel B model (7) as variable *Corruption: MP* is not available in round 2.

Table 3. Disaster exposure and local collective action: Baseline models

Panel A: Community focused engagements					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Dependent variables	*Contact: Loc Gov*	*Contact: MP*	*Contact as group*	*Community participation*	*Group membership*
exposed30_before	-0.002	-0.002	0.003	-0.000	0.001
	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)
exposed30_after	0.013*	0.002	-0.027**	-0.025***	0.012*
	(0.007)	(0.006)	(0.012)	(0.007)	(0.006)
Difference in Differences	-0.015	-0.004	0.030	0.025	-0.011
F-test: exposed30_before – exposed30_after = 0	4.029	0.570	5.027	12.768	2.528
P-value	0.045	0.451	0.025	0.001	0.112
Mean of dependent variable	0.250	0.117	0.580	0.651	0.229
Mean of exposed30_before	0.306	0.313	0.315	0.304	0.311
Mean of exposed30_after	0.089	0.087	0.083	0.112	0.087
Sample size	126,636	129,819	36,571	157,403	131,834
R-squared	0.093	0.068	0.113	0.162	0.096

Panel B: Politically oriented engagements					
	(6)	*(7)*	*(8)*	*(9)*	*(10)*
Dependent variables	*Interest in public affairs*	*Citizens should criticise gov*	*Attended a protest*	*Voting*	*Party affiliation*
exposed30_before	0.011**	-0.004	-0.002	-0.005**	-0.007
	(0.004)	(0.007)	(0.003)	(0.002)	(0.005)
exposed30_after	-0.018**	-0.037**	0.010**	0.000	-0.001
	(0.007)	(0.015)	(0.004)	(0.003)	(0.007)
Difference in Differences	0.029	0.034	-0.012	-0.005	-0.006
F-test: exposed30_before – exposed30_after = 0	15.884	4.886	6.895	2.521	0.685
P-value	0.001	0.027	0.009	0.112	0.408
Mean of dependent variable	0.607	0.290	0.107	0.936	0.612
Mean of exposed30_before	0.304	0.313	0.304	0.301	0.297
Mean of exposed30_after	0.112	0.057	0.111	0.115	0.115
Sample size	156,799	51,379	154,522	149,330	146,624
R-squared	0.069	0.102	0.045	0.101	0.129

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age2, gender and urban dummy), region and year fixed effects. The full set of results including the estimated coefficients for main control variables are reported in Appendix Table A14. The definitions of dependent variables are provided in Appendix Table A2. The sample includes Afrobarometer rounds 2 – 6, except models (3) and (7) since the variables *Contact as group* and *Citizens should criticise gov* are available in round 6 only.

As discussed earlier, another potential coping response by individuals living in disaster affected areas with deficient institutional settings and support is to become politically more engaged with the ultimate objective of removing the ineffective leaders from power – a possibility that is consistent with the democratic efficiency theory (Wittman, 1989; 1995). Panel B of Table 3 reports the results of our analysis on the link between disaster exposure and politically oriented engagements.

First, we look at individuals' interest in public affairs (model 6) and their views on appropriate behaviour of citizens towards government under a democracy (model 7). The results of this analysis point towards a shift in both outcomes in response to a disaster exposure. Relative to the pre-treatment group, disaster-exposed individuals are 2.9 percentage points more likely to report an *Interest in public affairs* (model 6). Moreover, the results of model 7 suggest that they are also 3.4 percentage points more likely to support the view that good citizens in a democracy should criticise their government– suggesting a rise of democratic beliefs in disaster-affected areas.

But are these beliefs put into action? The response based on our analysis is a 'no'. In fact, if anything, we observe a withdrawal from politically oriented actions in disaster-affected individuals which broadly supports the arguments by Hermet (1978) and Karklins (1986) whereby disengagement from traditional forms of political participation may be seen as a similarly powerful statement. The difference-in-differences results indicate that relative to individuals yet-to-be exposed to a disaster, individuals exposed to disaster are 1.2 percentage points less likely to have *Attended a protest* (model 8). When looking at *Voting* (model 9) and *Party affiliation* (model 10) as outcomes, the difference-in-differences estimates, while negative, are insignificant. Despite the lack of significance, the withdrawal from political engagement suffested by negative difference-in-differences estimate is in line with individual forms of political protest or evident traits of the democratic efficiency theory at play.

Overall, the results provide evidence of community focused engagements following a disaster. They show that following exposure to a disaster, individuals are more likely to contact their government or community leaders as a group rather than individually as well as attend a community meeting or gather to raise an issue. In terms of political engagements, there is no translation of increased interest in public affairs and shifts in democratic views into direct political action. In fact, our results point towards political disengagement in response to natural disasters.

2.6. Robustness Checks

The baseline analysis presented is based on employing a 30km spatial cut-off and a 15-year temporal cut-off to define the exposure to disasters. Admittedly, these cut-off distances are chosen arbitrarily, prompted by our focus on local effects of disasters. Our primary robustness check provides a comprehensive assessment of the robustness of the results to alternative combinations of spatial and temporal cut-offs. We re-run our analysis using 30 different definitions of exposure based on all possible combinations of spatial cut-offs in the range of 10-100km (at 10km intervals) with temporal cut-offs of 5, 10 and 15 years. Robustness checks to such wide range of definitions of exposure is well beyond what previous studies have employed, and potentially offer insights on choices of cut-offs when looking at the impact of natural disasters on different outcomes.

Figures A2-A6 in the appendix display the results of this analysis, showing the difference-in-differences estimates and the associated p-values corresponding to model estimates employing definitions of exposure based on different spatial and temporal cut-off combinations. The difference in differences estimates is presented in the form of blue circles increasing in size in line with greater positive differences and as red circles reducing in size with greater negative differences. The P-value is presented as a heat map with green indicating significance and red indicating insignificant results with degrees reflected in changes in shades.

Figure A2 shows the results for our economic vulnerability outcomes. The results are mostly robust to a battery of exposure definitions based on different spatial and temporal cut-off combinations, and any variations can be reasonably explained (for example – it is reasonable not to expect changes in food security with a disaster 100km away). Economic vulnerabilities appear to be most affected at moderate distances over a longer period.

Figures A3 and A4 report the same robustness checks for quality of governance. The results for government performance are mostly robust, with results for disapproval of performance becoming less significant the further away (both spatially and temporally) the individual is from the disaster. There is a more diverse spread of results for perceptions of corruption with our mapping showing significances at both closer and farther spatial distances, perhaps suggesting an influence from both local and regional government on individuals' perceptions. These variations do not negate the importance of our baseline results and instead confirm that regardless of the definition of exposure, there is consistent perception of ingrained institutional corruption.

We turn to Figures A5 and A6 for results on collective coping outcomes. We find that our results remain mostly robust for this set of outcomes and where significance is reduced or lost, we find that coefficient direction remains unchanged. Interestingly, we observe that the significance of effects on community action (contacting as a group, community participation and an interest in public affairs) are not immediate and much more robust in the longer term (10 – 15 years). Outcomes for contacting government officials show more irregularity, however results are robust for contacting local government at closer distances and robust for contacting regional MPs at farther distances further affirming a disengagement with government at respective levels.

Overall, this exercise suggests that our baseline results are predominantly robust to applying alternative spatial and temporal cut-offs in defining disaster exposure, and further reinforce our initial selection of a 30km and 15-year cut-off in baseline definition of exposure.

Our baseline analysis focuses on the incidence of a disaster, without differentiation by its type. Next, we introduce such differentiation by using our baseline specifications to conduct a difference-in-differences analysis in sub-samples of individuals based on the type of disasters they have had exposure to.[6] This is presented in Appendix Tables A3 – A8. As previously discussed, droughts are not included in our sample due to the absence of precise start dates associated with this type of disaster in the data, and thus we conduct analyses in sub-samples of individuals who have been exposed to floods and storms.[7] Tables A3 – A5 present our results based on the sub-sample of individuals exposed to floods. Most of our results are robust to restricting the sample to flood-exposed individuals, despite losing some significance in community-based engagement outcomes. Moreover, in this sub-sample we find that relative to yet-to-be exposed individuals, those who have been exposed to a flood are 2.4 percentage points less likely to have a Party affiliation – a result that further reinforces the earlier finding on political disengagement by disaster-exposed individuals. Tables A6 – A8 report our results based on the sub-sample of individuals who have been exposed to storms instead. As is the case of the analysis based on the previous sub-sample, these results are predominantly robust and mimic many of the findings of our baseline results, with some scattered changes in significance levels. Notably, results show that disaster-exposed individuals are 1.5 percentage points less likely to be registered to vote. Overall, based on this analysis, our results do not appear to be driven by any specific type of disaster.

Lastly, in an effort to tighten our identification setup further, we drop individuals with no exposure to a disaster from the sample, thereby simply drawing direct comparisons between exposed before and exposed after individuals. These results shown in Tables A9 – A11 suggest that despite some reduced significance levels, the nature of our results remains unchanged.

2.7. Conclusion

The frequency and impact of natural disasters is building, particularly affecting developing countries which do not have the necessary institutions or economic foundations for sufficient recovery. By

[6] We have also re-run our baseline models including controls for disaster type and found no significant differences with the baseline results.

[7] Only 1,081 individuals in our sample record exposure to other disaster types (extreme temperature events, mass movement (dry) landslide, volcanic activity, and wildfire) and we have not conducted analyses by these disaster types given the small sample sizes.

matching geo-referenced data on over 1000 disasters with data on over 175,000 individuals in 37 African countries, this paper offers novel insights on the coping responses of individuals exposed to natural disasters, thereby contributing significantly to the lack of systematic evidence in this area. Our analysis is based on employing a difference-in-differences design exploiting spatial and temporal distances to disasters, thereby allowing for robust close-to-causal inferences on the behavioural responses to disasters.

We show that exposure to natural disasters heightens the economic vulnerabilities experienced by individuals - they are more likely to have a negative outlook on their living conditions and report going without food. We also demonstrated that individuals exposed to a disaster are more likely to have a poor assessment of their government's performance and to have an increased perception of institutional corruption. In lieu of critical government support in response to a disaster, our analysis of coping responses shows that individuals exposed to a disaster lean towards community focused engagement and action. However, the dissatisfaction with government performance and legitimacy does not translate into political action directed towards removing ineffective government agents from office.

When a disaster highlights corruption and poor response, we'd ideally like to see the political system act to punish bad officials and replace them or at least change their behaviour. Such general mechanism appears to have been operative in the rise of Erdogan in Turkey, which followed an earlier earthquake, and in disciplining the second Bush administration in the US following Hurricane Katrina. This paper provides evidence that this mechanism is not at work in Africa. Individuals appear to turn to collective social rather than political action, suggesting that to some degree social bonds are a substitute for formal institutional structures. This evidence on the lack of political consequences of natural disasters adds to the larger body of work on political failures in Africa, including prominent stories about natural resource curse (Knutsen et al, 2017; Konte and Vincent, 2021) and ethnic divisions in politics (Eifert et al. 2010; Burgess et al. 2015). We show that natural disasters contribute to such failures, and in doing so offer insights that may add context and insights around the processes of disaster response and recovery.

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2.9. Appendix

Table A1. Breakdown of observations per country and round

	Afrobarometer Round					
Country	2	3	4	5	6	All
Algeria	0	0	0	1204	1200	2404
Benin	0	1198	1200	1200	1200	4798
Botswana	1200	1200	1200	1200	1200	6000
Burkina Faso	0	0	1200	1200	1200	3600
Burundi	0	0	0	1200	1200	2400
Cameroon	0	0	0	1200	1182	2382
Cape Verde	1283	1256	1264	1208	1200	6211
Cote D'Ivoire	0	0	0	1200	1199	2399
Egypt	0	0	0	1190	1198	2388
Ethiopia	0	0	0	2386	0	2386
Gabon	0	0	0	0	1198	1198
Ghana	1200	1197	1200	2400	2400	8397
Guinea	0	0	0	1200	1200	2400
Kenya	1199	1278	1104	2399	2397	8377
Lesotho	1200	1161	1200	1198	1200	5959
Liberia	0	0	1200	1199	1199	3598
Madagascar	0	1350	1350	1200	1200	5100
Malawi	2421	1200	1200	2408	2400	9629
Mali	1104	1244	1232	1200	1200	5980
Mauritius	0	0	0	1201	1200	2401
Morocco	0	0	0	1196	1200	2396
Mozambique	2428	1198	1200	2400	2400	9626
Namibia	1268	1200	1200	1200	1200	6068
Niger	0	0	0	1199	1200	2399
Nigeria	2398	2363	2324	2400	2400	11885
Sao Tome & Principe	0	0	0	0	1196	1196
Senegal	2400	1200	1200	1200	1200	7200
Sierra Leone	0	0	0	1190	1191	2381
South Africa	1400	2400	2400	2399	2390	10989
Sudan	0	0	0	1199	1200	2399
Swaziland	0	0	0	1200	1200	2400
Tanzania	1200	1304	1208	2400	2386	8498
Togo	0	0	0	1201	1200	2401

Tunisia	0	0	0	1200	1200	2400
Uganda	1200	2400	2431	2400	2400	10831
Zambia	1200	1200	1200	1200	1199	5999
Zimbabwe	1200	1048	1200	2400	2400	8248
Total	24301	25397	27713	53977	53935	185323

Source: authors’ compilation based on Afrobarometer data.

Table A2. Definitions of outcome variables

Outcomes	Variables	Definition	Rounds
Economic Vulnerability	Bad living conditions	0-1 binary variable; equals 1 if the individual rates their living conditions as fairly bad or very bad and equals 0 if the individual rates their living conditions as neither good nor bad, fairly good, or very good.	2 – 6
	Not employed	0-1 binary variable; equals 1 if the individual is either unemployed and looking for a job or not looking for a job and equals 0 if the individual is employed.	2 – 6
	Going without food	0-1 binary variable; equals 1 if the individual has reported going without food in the past 12 months and equals 0 if they have not.	2 – 6
	Frequency without food	0-1 binary variable; equals 1 if the individual has gone without food more frequently than the reported average equals 0 if they have gone without food below the reported frequency average.	6
	Food shortage a problem	0-1 binary variable; equals 1 if the individual has identified food shortage as one of their country's three most important problems and equals 0 if they have not.	2 – 6
Government Performance	Disapproval of performance: Loc Gov	0-1 binary variable; equals 1 if the individual either disapproves or strongly disapproves of performance and equals 0 if the individual approves or strongly approves of performance.	2 – 6
	Disapproval of performance: MP	0-1 binary variable; equals 1 if the individual either disapproves or strongly disapproves of performance and equals 0 if the individual approves or strongly approves of performance.	2 – 6
	Management of economy a problem	0-1 binary variable; equals 1 if the individual has identified management of the economy as one of their country's three most important problems and equals 0 if they have not.	2 – 6
	Difficulty accessing services	0-1 binary variable; equals 1 if the individual has reported difficulty in accessing any of the following services: schooling, medical treatment, identity documents, household services, help from police, or assistance from the courts in the past 12 months and 0 if they have not.	2, 3, 5, 6

Perceptions of Corruption	Increase in corruption	0-1 binary variable; equals 1 if the individual believes corruption has increased somewhat or increased a lot and equals 0 if they believe corruption has stayed the same, decreased somewhat or decreased a lot.	6
	Corruption: Gov Official	0-1 binary variable; equals 1 if the individual believes that some of them, most of them, or all of them are involved in corruption, and equals 0 if they believe none of them are.	2 – 6
	Corruption: MP	0-1 binary variable; equals 1 if the individual believes that some of them, most of them, or all of them are involved in corruption, and equals 0 if they believe none of them are.	3 – 6
	Corruption: Police	0-1 binary variable; equals 1 if the individual believes that some of them, most of them, or all of them are involved in corruption, and equals 0 if they believe none of them are.	2 – 6
	Corruption a problem	0-1 binary variable; equals 1 if the individual has identified corruption as one of their country's three most important problems and equals 0 if they have not.	2 – 6
Community-Focused Engagements	Contact: Loc Gov	0-1 binary variable; equals 1 if over the past year, the individual has contacted local government only once, a few times or often, and equals 0 if they never did.	2 – 6
	Contact: MP	0-1 binary variable; equals 1 if over the past year, the individual has contacted their MP only once, a few times or often, and equals 0 if they never did.	2 – 6
	Contact as group	0-1 binary variable; equals 1 if the individual reports contacting leaders as a group and equals 0 if they contacted them alone.	6
	Community participation	0-1 binary variable; equals 1 if the individual reports attending a community meeting or getting together with others to raise an issue in the past year and equals 0 if they did neither of these.	2 – 6
	Group membership	0-1 binary variable; equals 1 if the individual reports being an active member or official leader of a voluntary association or community group and equals 0 if they are an inactive member or not a member.	2 – 6
Politically Oriented Engagements	Interest in public affairs	0-1 binary variable; equals 1 if the individual reports that they are somewhat interested or very interested in public affairs and equals 0 if the individual reports they are not very interested or not at all interested in public affairs.	2 – 6

Citizens should criticise gov	0-1 binary variable; equals 1 if the individual believes a good citizen in a democracy should criticise government and equals 0 if the individual believes a good citizen avoids criticising government.	6
Attended a protest	0-1 binary variable; equals 1 if the individual responded yes, once or twice, yes, several times or yes, often to attending a protest in the past year and equals 0 if they responded no, would never do this or no, but would do if had the chance.	2 – 6
Voting	0-1 binary variable; equals 1 if the individual reports being registered to vote at the last national election and equals 0 if they were not registered.	2 – 6
Party affiliation	0-1 binary variable; equals 1 if the individual indicates they feel affiliated to a political party and equals 0 if they do not.	2 – 6

Source: authors' compilation based on Afrobarometer data.

Table A3. Disaster exposure and economic vulnerability: Sub-sample of floods

	(1)	(2)	(3)	(4)	(5)
	Bad living conditions	*Not employed*	*Going without food*	*Frequency without food*	*Food shortage a problem*
exposed30_before	-0.000	-0.011**	-0.003	0.012	0.010**
	(0.005)	(0.005)	(0.006)	(0.008)	(0.005)
exposed30_after	0.009	-0.036***	0.003	-0.029	-0.006
	(0.008)	(0.009)	(0.008)	(0.020)	(0.007)
Difference in Differences	-0.009	0.025	-0.007	0.041	0.016
F-test: exposed30_before – exposed30_after = 0	1.206	6.692	0.562	4.004	4.498
P-value	0.272	0.010	0.454	0.045	0.034
Mean of dep variable	0.476	0.635	0.493	0.568	0.180
No. obs.	157,516	157,720	158,034	52,277	158,344
R-squared	0.109	0.172	0.142	0.229	0.171

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference in differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except model (4) since the variable *Frequency without food* is available in round 6 only.

Table A4. Disaster exposure and quality of governance: Sub-sample of floods

Panel A: Government performance				
	(1)	*(2)*	*(3)*	*(4)*
	Disapproval of performance: Loc Gov	*Disapproval of performance: MP*	*Management of economy a problem*	*Difficulty accessing services*
exposed30_before	0.007	0.020***	0.010***	-0.000
	(0.006)	(0.006)	(0.004)	(0.004)
exposed30_after	-0.011	-0.011	-0.004	-0.022***
	(0.009)	(0.009)	(0.005)	(0.007)
Difference in Differences	0.018	0.031	0.014	0.022
F-test: exposed30_before – exposed30_after = 0	3.515	9.778	6.254	9.015
P-value	0.067	0.002	0.012	0.003
Mean of dep variable	0.457	0.480	0.133	0.849
No. obs.	132,267	136,891	158,344	107,429
R-squared	0.097	0.102	0.079	0.085

Panel B: Perceptions of corruption					
	(5)	*(6)*	*(7)*	*(8)*	*(9)*
	Increase in corruption	*Corruption: Gov Official*	*Corruption: MP*	*Corruption: Police*	*Corruption a problem*
exposed30_before	0.011	0.011***	0.015***	0.010***	0.008***
	(0.008)	(0.003)	(0.004)	(0.003)	(0.003)
exposed30_after	-0.027	0.009*	0.011*	0.012***	0.007
	(0.017)	(0.005)	(0.006)	(0.004)	(0.004)
Difference in Differences	0.038	0.002	0.003	-0.002	0.001
F-test: exposed30_before – exposed30_after = 0	4.279	0.209	0.255	0.266	0.023
P-value	0.039	0.648	0.613	0.606	0.880
Mean of dep variable	0.620	0.895	0.860	0.903	0.114
No. obs.	49,711	136,771	131,649	142,367	158,344
R-squared	0.161	0.086	0.104	0.082	0.070

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except Panel A model (4) as the variable

Difficulty accessing services is not available in round 4, Panel B model (5) since the variable *Increase in corruption* is available in round 6 only, and Panel B model (7) as variable *Corruption: MP* is not available in round 2.

Table A5. Disaster exposure and local collective action: Sub-sample of floods

Panel A: Community focused engagements					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Contact: Loc Gov	*Contact: MP*	*Contact as group*	*Community participation*	*Group membership*
exposed30_before	-0.001	0.000	0.001	0.003	-0.002
	(0.005)	(0.003)	(0.009)	(0.005)	(0.004)
exposed30_after	0.015*	0.006	-0.022	0.002	0.010
	(0.008)	(0.006)	(0.014)	(0.007)	(0.007)
Difference in Differences	-0.015	-0.006	0.023	0.001	-0.011
F-test: exposed30_before – exposed30_after = 0	3.156	0.869	2.261	0.026	2.054
P-value	0.076	0.351	0.133	0.871	0.152
Mean of dep variable	0.250	0.117	0.580	0.651	0.229
No. obs.	126,636	129,819	36,571	157,403	131,834
R-squared	0.093	0.068	0.113	0.162	0.096
Panel B: Politically oriented engagements					
	(6)	*(7)*	*(8)*	*(9)*	*(10)*
	Interest in public affairs	*Citizens should criticise gov*	*Attended a protest*	*Voting*	*Party affiliation*
exposed30_before	0.009*	-0.002	-0.003	-0.003	-0.004
	(0.005)	(0.008)	(0.003)	(0.002)	(0.005)
exposed30_after	-0.006	-0.038*	0.002	-0.002	0.020***
	(0.008)	(0.021)	(0.005)	(0.003)	(0.007)
Difference in Differences	0.014	0.036	-0.005	-0.002	-0.024
F-test: exposed30_before – exposed30_after = 0	3.209	2.685	1.042	0.203	8.931
P-value	0.073	0.101	0.307	0.652	0.003
Mean of dep variable	0.607	0.290	0.107	0.936	0.612
No. obs.	156,799	51,379	154,522	149,330	146,624
R-squared	0.069	0.102	0.045	0.101	0.130

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except models (3) and (7) since the variables *Contact as group* and *Citizens should criticise gov* are available in round 6 only.

Table A6. Disaster exposure and economic vulnerability: Sub-sample of storms

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Bad living conditions	*Not employed*	*Going without food*	*Frequency without food*	*Food shortage a problem*
exposed30_before	0.005	0.019*	-0.014	-0.011	0.002
	(0.011)	(0.012)	(0.011)	(0.016)	(0.007)
exposed30_after	-0.127***	-0.008	-0.098***	-0.045**	-0.035***
	(0.021)	(0.016)	(0.017)	(0.021)	(0.011)
Difference in Differences	0.132	0.027	0.084	0.033	0.037
F-test: exposed30_before – exposed30_after = 0	30.070	2.030	16.971	1.665	8.925
P-value	0.001	0.154	0.001	0.197	0.003
Mean of dep variable	0.476	0.635	0.493	0.568	0.180
No. obs.	157,516	157,720	158,034	52,277	158,344
R-squared	0.110	0.171	0.142	0.229	0.171

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference in differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except model (4) since the variable *Frequency without food* is available in round 6 only.

Table A7. Disaster exposure and quality of governance: Sub-sample of storms

Panel A: Government performance

	(1)	(2)	(3)	(4)
	Disapproval of performance: Loc Gov	*Disapproval of performance: MP*	*Management of economy a problem*	*Difficulty accessing services*
exposed30_before	-0.042***	-0.021	-0.004	0.030***
	(0.012)	(0.013)	(0.006)	(0.010)
exposed30_after	-0.048***	-0.048***	-0.034***	-0.032**
	(0.017)	(0.016)	(0.007)	(0.014)
Difference in Differences	0.006	0.027	0.031	0.062
F-test: exposed30_before – exposed30_after = 0	0.099	1.967	11.769	14.753
P-value	0.753	0.161	0.001	0.001
Mean of dep variable	0.457	0.480	0.133	0.849
No. obs.	132,267	136,891	158,344	107,429
R-squared	0.097	0.102	0.079	0.085

Panel B: Perceptions of corruption

	(5)	(6)	(7)	(8)	(9)
	Increase in corruption	*Corruption: Gov Official*	*Corruption: MP*	*Corruption: Police*	*Corruption a problem*
exposed30_before	-0.001	-0.021***	-0.026***	-0.011*	-0.007
	(0.014)	(0.007)	(0.008)	(0.006)	(0.006)
exposed30_after	-0.040*	-0.039***	-0.042***	-0.039***	-0.029***
	(0.022)	(0.011)	(0.012)	(0.011)	(0.008)
Difference in Differences	0.039	0.018	0.016	0.027	0.022
F-test: exposed30_before – exposed30_after = 0	2.267	2.138	1.351	5.177	5.975
P-value	0.132	0.144	0.245	0.023	0.015
Mean of dep variable	0.620	0.895	0.860	0.903	0.114
No. obs.	49,711	136,771	131,649	142,367	158,344
R-squared	0.161	0.086	0.104	0.082	0.070

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except Panel A model (4) as the variable

Difficulty accessing services is not available in round 4, Panel B model (5) since the variable *Increase in corruption* is available in round 6 only, and Panel B model (7) as variable *Corruption: MP* is not available in round 2.

Table A8. Disaster exposure and local collective action: Sub-sample of storms

Panel A: Community focused engagements					
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Contact: Loc Gov	*Contact: MP*	*Contact as group*	*Community participation*	*Group membership*
exposed30_before	0.000	-0.008	0.026	0.008	0.007
	(0.011)	(0.008)	(0.019)	(0.010)	(0.008)
exposed30_after	0.008	-0.018*	0.006	-0.093***	0.017
	(0.014)	(0.010)	(0.028)	(0.018)	(0.013)
Difference in Differences	-0.008	0.010	0.021	0.102	-0.010
F-test: exposed30_before – exposed30_after = 0	0.227	0.647	0.392	27.158	0.491
P-value	0.633	0.421	0.531	0.001	0.483
Mean of dep variable	0.250	0.117	0.580	0.651	0.229
No. obs.	126,636	129,819	36,571	157,403	131,834
R-squared	0.093	0.068	0.113	0.162	0.096
Panel B: Politically oriented engagements					
	(6)	*(7)*	*(8)*	*(9)*	*(10)*
	Interest in public affairs	*Citizens should criticise gov*	*Attended a protest*	*Voting*	*Party affiliation*
exposed30_before	0.026***	-0.001	0.003	-0.008*	-0.002
	(0.009)	(0.017)	(0.006)	(0.004)	(0.013)
exposed30_after	-0.055***	-0.053***	0.023***	0.007	-0.061***
	(0.017)	(0.018)	(0.008)	(0.005)	(0.015)
Difference in Differences	0.080	0.052	-0.020	-0.015	0.059
F-test: exposed30_before – exposed30_after = 0	19.147	4.760	4.215	5.846	10.418
P-value	0.001	0.029	0.040	0.016	0.001
Mean of dep variable	0.607	0.290	0.107	0.936	0.612
No. obs.	156,799	51,379	154,522	149,330	146,624
R-squared	0.069	0.102	0.045	0.101	0.130

Note: *** $p < .01$, **$p < .05$, * $p < .1$. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except models (3) and (7) since the variables *Contact as group* and *Citizens should criticise gov* are available in round 6 only.

Table A9. Disaster exposure and economic vulnerability: Sub-sample excluding individuals with no exposure

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Bad living conditions	*Not employed*	*Going without food*	*Frequency without food*	*Food shortage a problem*
exposed30_before	-0.003	0.019*	-0.007	0.048***	0.018**
	(0.011)	(0.010)	(0.010)	(0.017)	(0.009)
Mean of dep variable	0.486	0.631	0.490	0.572	0.193
No. obs.	65,479	65,591	65,682	19,364	65,781
R-squared	0.114	0.169	0.141	0.230	0.152

Note: *** $p < .01$, **$p < .05$, * $p < .1$. Standard errors, clustered at the PSU level, are in parenthesis. The base category are the exposed30_after individuals (those exposed to a disaster after the survey). All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except model (4) since the variable *Frequency without food* is available in round 6 only.

Table A10. Disaster exposure and quality of governance: Sub-sample excluding individuals with no exposure

Panel A: Government performance				
	(1)	*(2)*	*(3)*	*(4)*
	Disapproval of performance: Loc Gov	*Disapproval of performance: MP*	*Management of economy a problem*	*Difficulty accessing services*
exposed30_before	0.032***	0.035***	0.023***	0.023***
	(0.010)	(0.010)	(0.006)	(0.008)
Mean of dep variable	0.448	0.482	0.137	0.858
No. obs.	54,840	56,985	65,781	43,604
R-squared	0.108	0.107	0.086	0.089

Panel B: Perceptions of corruption					
	(5)	*(6)*	*(7)*	*(8)*	*(9)*
	Increase in corruption	*Corruption: Gov Official*	*Corruption: MP*	*Corruption: Police*	*Corruption a problem*
exposed30_before	0.009	0.009	0.005	0.005	0.010*
	(0.019)	(0.006)	(0.007)	(0.006)	(0.005)
Mean of dep variable	0.640	0.894	0.860	0.904	0.114
No. obs.	18,325	55,819	54,072	58,342	65,781
R-squared	0.159	0.101	0.122	0.095	0.071

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The base category are the exposed30_after individuals (those exposed to a disaster after the survey). All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except Panel A model (4) as the variable *Difficulty accessing services* is not available in round 4, Panel B model (5) since the variable *Increase in corruption* is available in round 6 only, and Panel B model (7) as variable *Corruption: MP* is not available in round 2.

Table A11. Disaster exposure and local collective action: Sub-sample excluding individuals with no exposure

	Panel A: Community focused engagements				
	(1)	*(2)*	*(3)*	*(4)*	*(5)*
	Contact: Loc Gov	*Contact: MP*	*Contact as group*	*Community participation*	*Group membership*
exposed30_before	-0.015*	-0.001	0.023	0.010	-0.009
	(0.009)	(0.006)	(0.016)	(0.008)	(0.008)
Mean of dep variable	0.241	0.114	0.567	0.656	0.232
No. obs.	50,084	51,878	14,550	65,462	52,437
R-squared	0.098	0.070	0.126	0.161	0.096
	Panel B: Politically oriented engagements				
	(6)	*(7)*	*(8)*	*(9)*	*(10)*
	Interest in public affairs	*Citizens should criticise gov*	*Attended a protest*	*Voting*	*Party affiliation*
exposed30_before	0.020**	0.033	-0.011**	-0.002	-0.017*
	(0.008)	(0.021)	(0.005)	(0.004)	(0.009)
Mean of dep variable	0.613	0.316	0.105	0.936	0.611
No. obs.	65,251	19,017	64,247	62,119	60,325
R-squared	0.065	0.120	0.050	0.112	0.112

Note: *** $p < .01$, ** $p < .05$, * $p < .1$. Standard errors, clustered at the PSU level, are in parenthesis. The base category are the exposed30_after individuals (those exposed to a disaster after the survey). All regressions include baseline controls (age, age^2, gender and urban dummy), region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except models (3) and (7) since the variables *Contact as group* and *Citizens should criticise gov* are available in round 6 only.

Table A12. Disaster exposure and economic vulnerability: Baseline models with expanded set of results

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Dependent variables	*Bad living conditions*	*Not employed*	*Going without food*	*Frequency without food*	*Food shortage a problem*
exposed30_before	-0.004	-0.006	-0.010*	0.007	0.008*
	(0.005)	(0.005)	(0.005)	(0.007)	(0.004)
exposed30_after	-0.030***	-0.030***	-0.026***	-0.028*	-0.014**
	(0.009)	(0.008)	(0.008)	(0.014)	(0.006)
Age	0.009***	-0.031***	0.005***	0.001*	-0.001***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Age2	-0.070***	0.357***	-0.043***	-0.006	0.023***
	(0.005)	(0.006)	(0.005)	(0.008)	(0.004)
Male (gender dummy)	-0.006***	-0.132***	-0.019***	-0.011***	-0.033***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Urban dummy	-0.066***	-0.082***	-0.109***	-0.092***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)
Difference in Differences	0.026	0.024	0.016	0.034	0.022
F-test: exposed30_before – exposed30_after = 0	8.404	8.209	3.754	5.263	10.991
P-value	0.004	0.004	0.053	0.022	0.001
Mean of dep variable	0.476	0.635	0.493	0.568	0.180
Mean of exposed30_before	0.303	0.304	0.304	0.314	0.303
Mean of exposed30_after	0.112	0.112	0.112	0.057	0.112
Sample size	157,516	157,720	158,034	52,277	158,344
R-squared	0.109	0.172	0.142	0.229	0.171

Note: *** $p < .01$, **$p < .05$, * $p < .1$. Standard errors, clustered at the PSU level, are in parenthesis. The difference in differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except model (4) since the variable *Frequency without food* is available in round 6 only.

Table A13. Disaster exposure and quality of governance: Baseline models with expanded set of results

Panel A: Government performance

	(1)	(2)	(3)	(4)
Dependent variables	*Disapproval of performance: Loc Gov*	*Disapproval of performance: MP*	*Management of economy a problem*	*Difficulty accessing services*
exposed30_before	-0.002	0.012**	0.008**	0.005
	(0.005)	(0.006)	(0.003)	(0.004)
exposed30_after	-0.024***	-0.022***	-0.012***	-0.024***
	(0.008)	(0.008)	(0.004)	(0.006)
Age	0.002***	0.003***	0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Age2	-0.033***	-0.047***	-0.016***	0.019***
	(0.005)	(0.005)	(0.003)	(0.005)
Male (gender dummy)	0.018***	0.020***	0.020***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)
Urban dummy	0.030***	0.019***	0.039***	0.011***
	(0.004)	(0.004)	(0.003)	(0.003)
Difference in Differences	0.022	0.034	0.019	0.029
F-test: exposed30_before – exposed30_after = 0	6.878	15.162	16.266	19.249
P-value	0.009	0.001	0.001	0.001
Mean of dep variable	0.457	0.480	0.133	0.849
Mean of exposed30_before	0.300	0.305	0.303	0.301
Mean of exposed30_after	0.115	0.111	0.112	0.104
Sample size	132,267	136,891	158,344	107,429
R-squared	0.097	0.102	0.079	0.085

Panel B: Perceptions of corruption

	(5)	(6)	(7)	(8)	(9)
Dependent variables	*Increase in corruption*	*Corruption: Gov Official*	*Corruption: MP*	*Corruption: Police*	*Corruption a problem*
exposed30_before	0.008	0.005*	0.008**	0.005**	0.005**
	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)
exposed30_after	-0.027**	-0.006	-0.002	-0.004	-0.001
	(0.013)	(0.005)	(0.005)	(0.004)	(0.004)

Age	0.002***	0.001***	0.000	0.001***	-0.001**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age2	-0.025***	-0.020***	-0.017***	-0.022***	-0.000
	(0.008)	(0.004)	(0.004)	(0.004)	(0.003)
Male (gender dummy)	0.005	0.012***	0.007***	0.012***	0.027***
	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)
Urban dummy	0.009	0.030***	0.035***	0.030***	0.048***
	(0.006)	(0.002)	(0.003)	(0.002)	(0.003)
Difference in Differences	0.035	0.011	0.009	0.009	0.007
F-test: exposed30_before – exposed30_after = 0	6.104	4.531	2.586	4.152	2.413
P-value	0.014	0.033	0.108	0.042	0.120
Mean of dep variable	0.620	0.895	0.860	0.903	0.114
Mean of exposed30_before	0.314	0.308	0.311	0.308	0.303
Mean of exposed30_after	0.055	0.100	0.100	0.102	0.112
Sample size	49,711	136,771	131,649	142,367	158,344
R-squared	0.161	0.086	0.104	0.082	0.070

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except Panel A model (4) as the variable *Difficulty accessing services* is not available in round 4, Panel B model (5) since the variable *Increase in corruption* is available in round 6 only, and Panel B model (7) as variable *Corruption: MP* is not available in round 2.

Table A14. Disaster exposure and local collective action: Baseline models with expanded set of results

Panel A: Community focused engagements

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Dependent variables	*Contact: Loc Gov*	*Contact: MP*	*Contact as group*	*Community participation*	*Group membership*
exposed30_before	-0.002	-0.002	0.003	-0.000	0.001
	(0.004)	(0.003)	(0.008)	(0.004)	(0.004)
exposed30_after	0.013*	0.002	-0.027**	-0.025***	0.012*
	(0.007)	(0.006)	(0.012)	(0.007)	(0.006)
Age	0.015***	0.006***	0.000	0.017***	0.012***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Age2	-0.140***	-0.057***	-0.001	-0.162***	-0.110***
	(0.005)	(0.004)	(0.010)	(0.005)	(0.005)
Male (gender dummy)	0.103***	0.049***	0.027***	0.099***	0.052***
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Urban dummy	-0.039***	-0.012***	-0.058***	-0.084***	-0.031***
	(0.004)	(0.003)	(0.007)	(0.004)	(0.003)
Difference in Differences	-0.015	-0.004	0.030	0.025	-0.011
F-test: exposed30_before – exposed30_after = 0	4.029	0.570	5.027	12.768	2.528
P-value	0.045	0.451	0.025	0.001	0.112
Mean of dependent variable	0.250	0.117	0.580	0.651	0.229
Mean of exposed30_before	0.306	0.313	0.315	0.304	0.311
Mean of exposed30_after	0.089	0.087	0.083	0.112	0.087
Sample size	126,636	129,819	36,571	157,403	131,834
R-squared	0.093	0.068	0.113	0.162	0.096

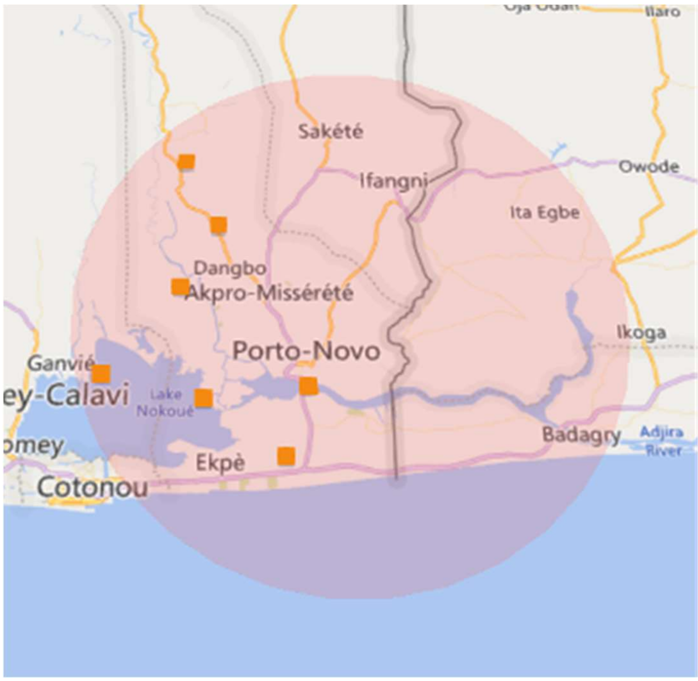
Panel B: Politically oriented engagements

	(6)	*(7)*	*(8)*	*(9)*	*(10)*
Dependent variables	*Interest in public affairs*	*Citizens should criticise gov*	*Attended a protest*	*Voting*	*Party affiliation*
exposed30_before	0.011**	-0.004	-0.002	-0.005**	-0.007
	(0.004)	(0.007)	(0.003)	(0.002)	(0.005)
exposed30_after	-0.018**	-0.037**	0.010**	0.000	-0.001
	(0.007)	(0.015)	(0.004)	(0.003)	(0.007)

Age	0.007***	-0.000	0.001***	0.015***	0.009***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Age2	-0.073***	0.002	-0.021***	-0.139***	-0.085***
	(0.005)	(0.008)	(0.003)	(0.003)	(0.005)
Male (gender dummy)	0.126***	0.006*	0.040***	0.009***	0.068***
	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)
Urban dummy	0.009**	0.009*	0.015***	-0.002	-0.039***
	(0.004)	(0.005)	(0.002)	(0.002)	(0.004)
Difference in Differences	0.029	0.034	-0.012	-0.005	-0.006
F-test: exposed30_before – exposed30_after = 0	15.884	4.886	6.895	2.521	0.685
P-value	0.001	0.027	0.009	0.112	0.408
Mean of dependent variable	0.607	0.290	0.107	0.936	0.612
Mean of exposed30_before	0.304	0.313	0.304	0.301	0.297
Mean of exposed30_after	0.112	0.057	0.111	0.115	0.115
Sample size	156,799	51,379	154,522	149,330	146,624
R-squared	0.069	0.102	0.045	0.101	0.129

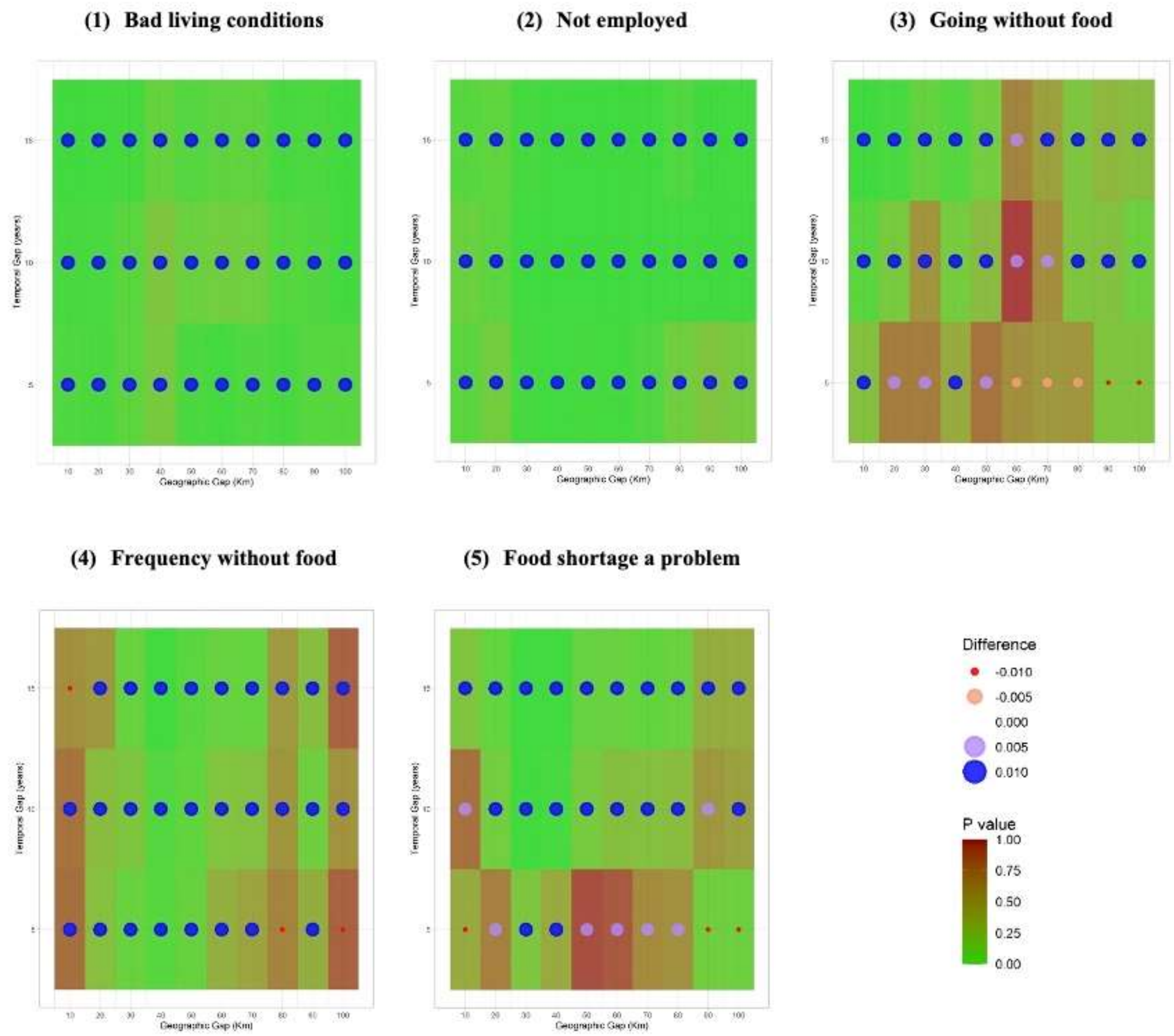
Note: *** $p < .01$, ** $p < .05$, * $p < .1$. Standard errors, clustered at the PSU level, are in parenthesis. The difference-in-differences term gives the difference between individuals exposed to a disaster before and after the interview; and we present the associated F-test and p-value of the F-test. All regressions include region and year fixed effects. The sample includes Afrobarometer rounds 2 – 6, except models (3) and (7) since the variables *Contact as group* and *Citizens should criticise gov* are available in round 6 only.

Figure A1. Linking disasters to primary sampling units of individual respondents: An example of Adjarra, Benin



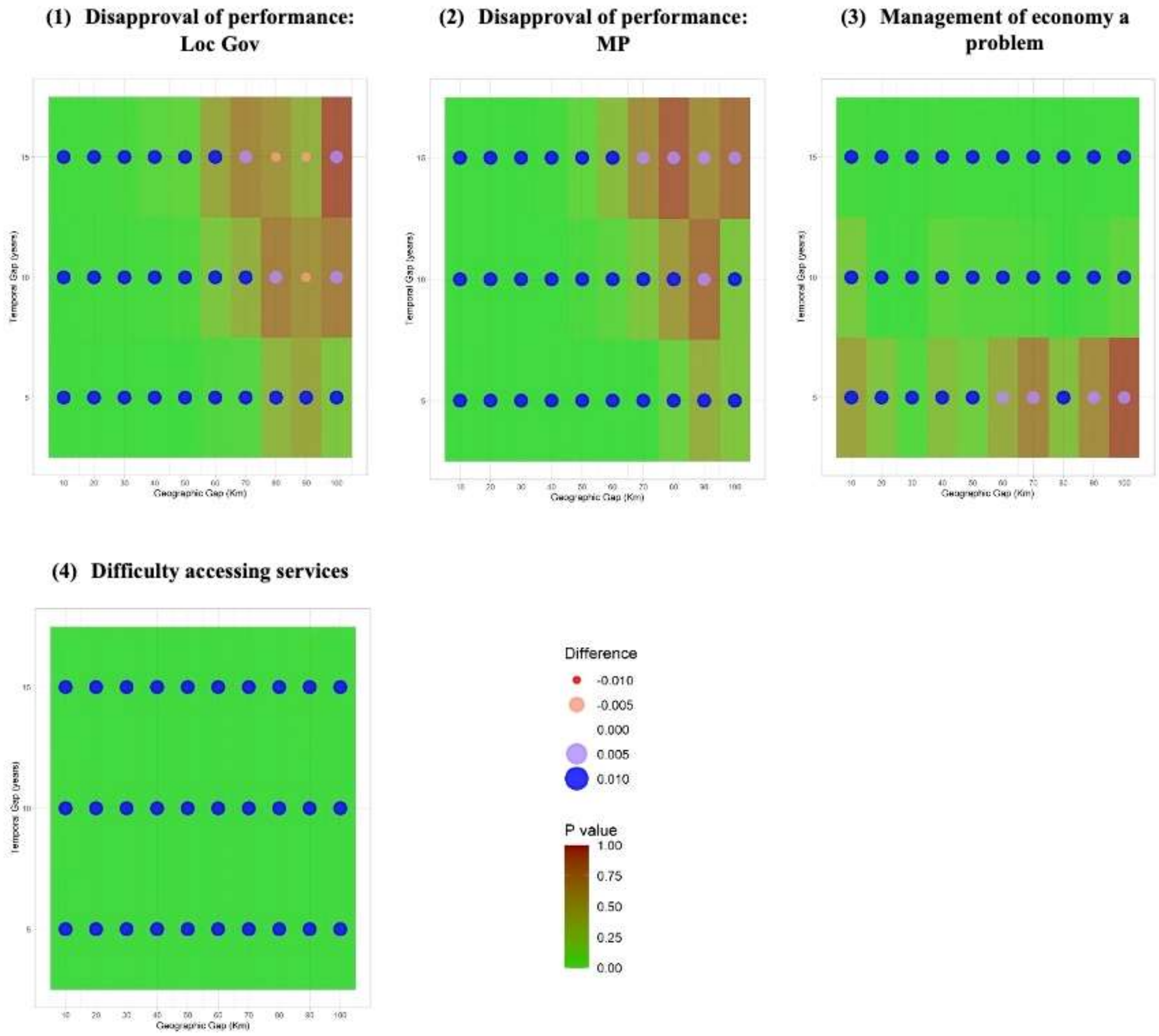
Note: The orange squares indicate instances of disasters within a 30km radius of the PSU (Adjarra, Benin) indicated by the red circle.

Figure A2. Disaster exposure and economic vulnerability: Robustness to definition of exposure



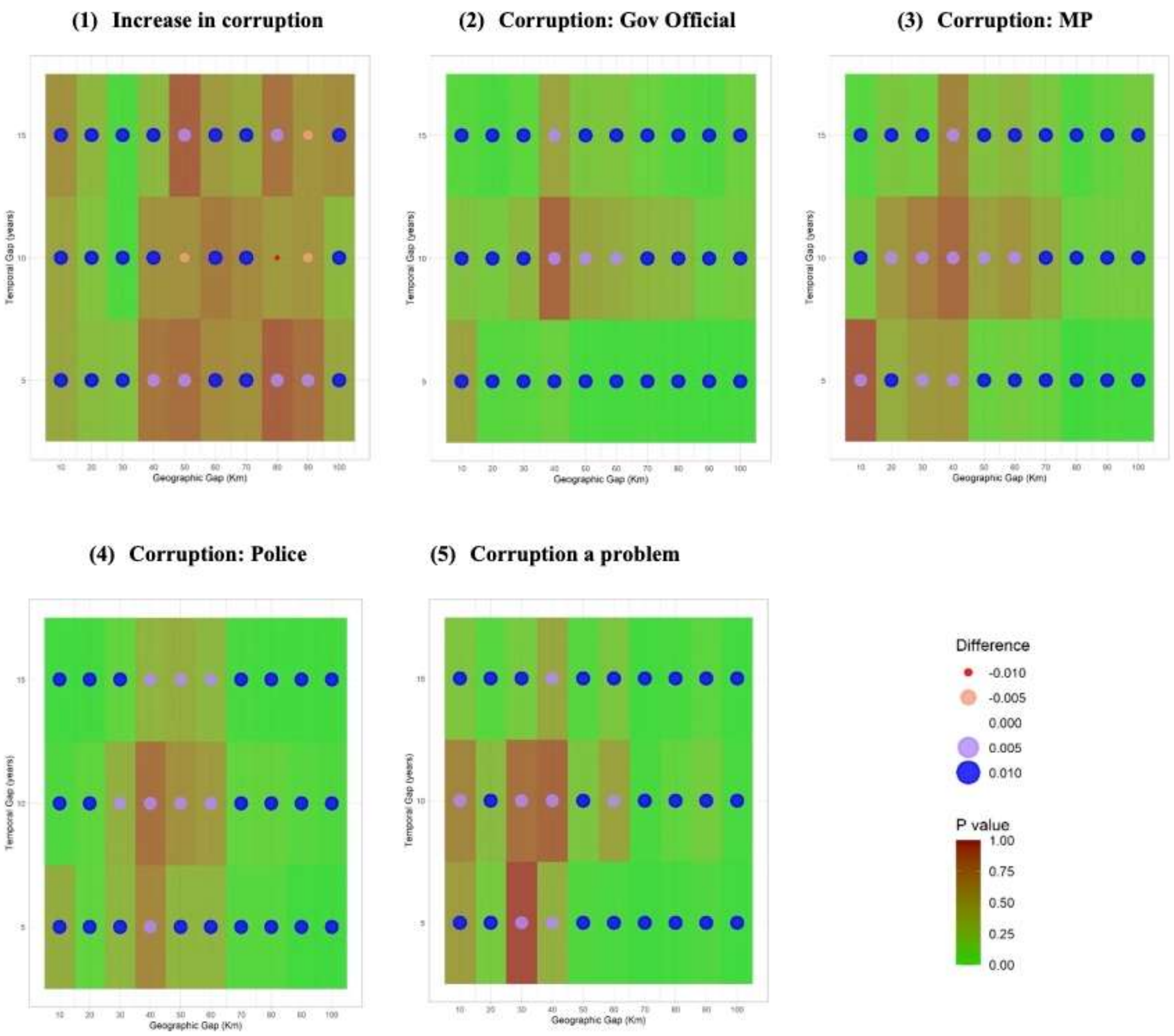
Note: The figures show the difference-in-differences estimates and the associated p-values corresponding to model estimates employing definitions of exposure based on different spatial and temporal cut-off combinations. The difference in differences estimates is presented in the form of blue circles increasing in size in line with greater positive differences and as red circles reducing in size with greater negative differences. The P-value is presented as a heat map with green indicating significance and red indicating insignificant results with degrees reflected in changes in shades.

Figure A3. Disaster exposure and quality of governance (government performance): Robustness to definition of exposure



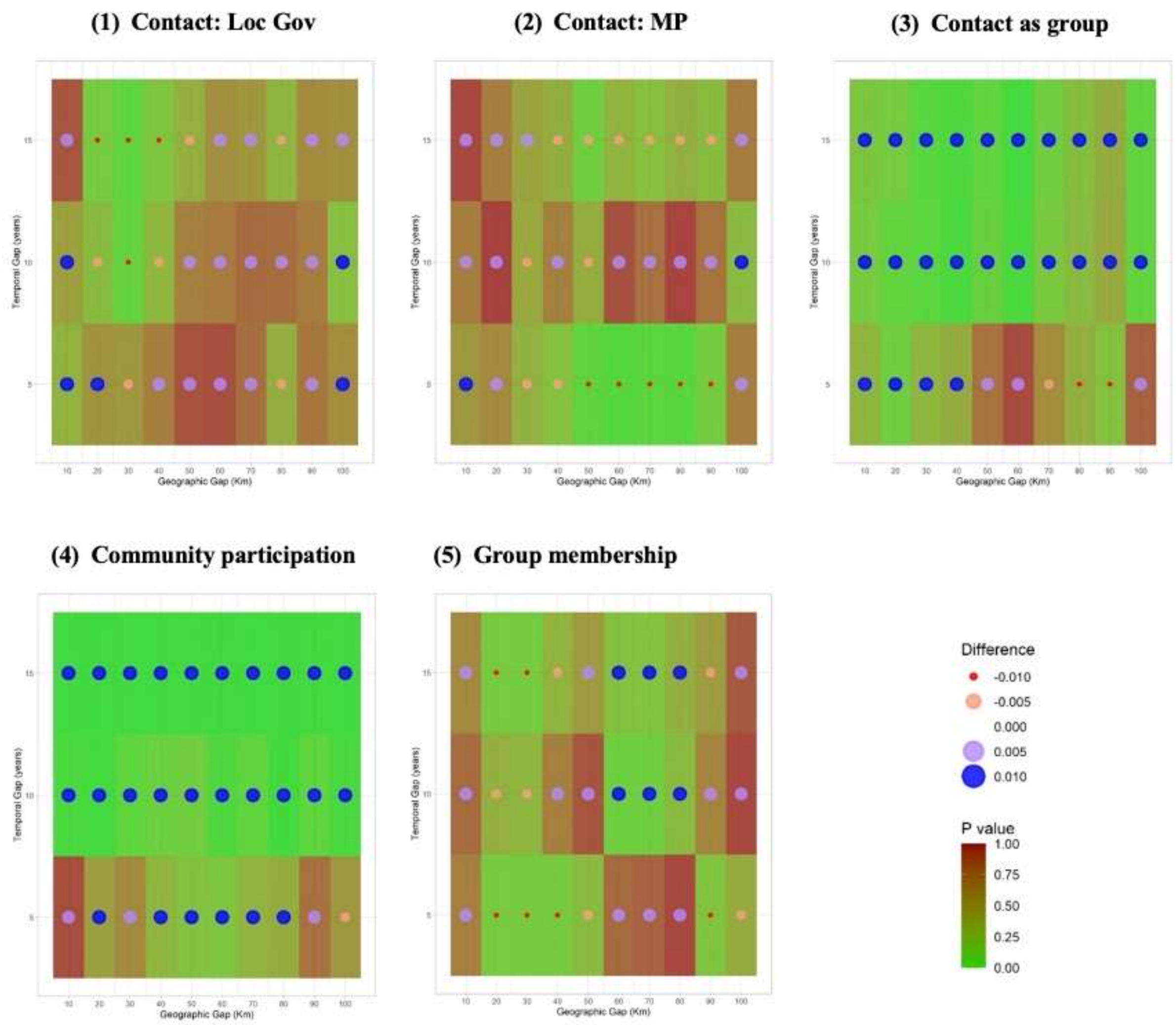
Note: The figures show the difference-in-differences estimates and the associated p-values corresponding to model estimates employing definitions of exposure based on different spatial and temporal cut-off combinations. The difference in differences estimates is presented in the form of blue circles increasing in size in line with greater positive differences and as red circles reducing in size with greater negative differences. The P-value is presented as a heat map with green indicating significance and red indicating insignificant results with degrees reflected in changes in shades.

Figure A4. Disaster exposure and quality of governance (perceptions of corruption): Robustness to definition of exposure



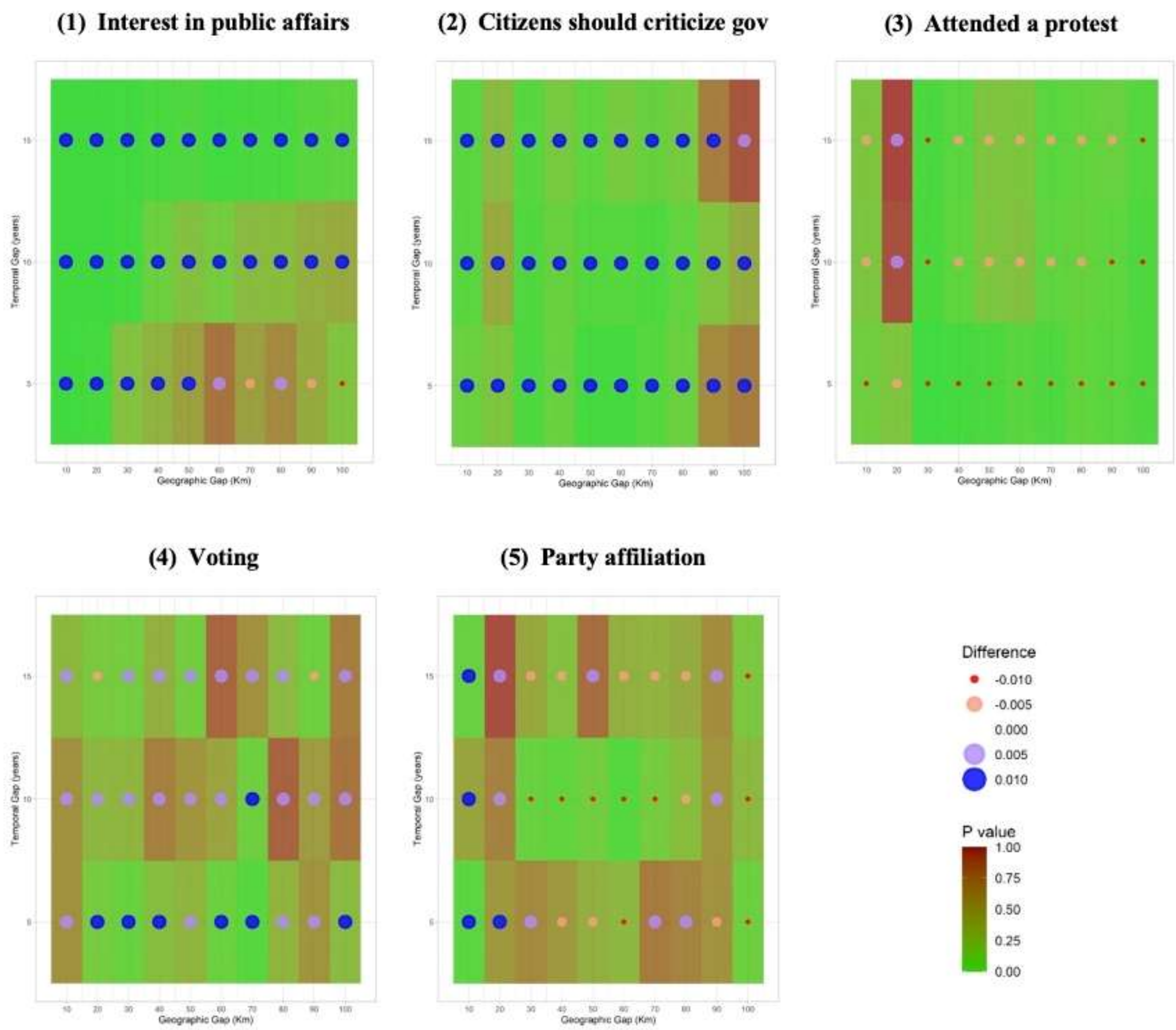
Note: The figures show the difference-in-differences estimates and the associated p-values corresponding to model estimates employing definitions of exposure based on different spatial and temporal cut-off combinations. The difference in differences estimates is presented in the form of blue circles increasing in size in line with greater positive differences and as red circles reducing in size with greater negative differences. The P-value is presented as a heat map with green indicating significance and red indicating insignificant results with degrees reflected in changes in shades.

Figure A5. Disaster exposure and local collective action (community focused engagements): Robustness to definition of exposure



Note: The figures show the difference-in-differences estimates and the associated p-values corresponding to model estimates employing definitions of exposure based on different spatial and temporal cut-off combinations. The difference in differences estimates is presented in the form of blue circles increasing in size in line with greater positive differences and as red circles reducing in size with greater negative differences. The P-value is presented as a heat map with green indicating significance and red indicating insignificant results with degrees reflected in changes in shades.

Figure A6. Disaster exposure and local collective action (politically oriented engagements): Robustness to definition of exposure



Note: The figures show the difference-in-differences estimates and the associated p-values corresponding to model estimates employing definitions of exposure based on different spatial and temporal cut-off combinations. The difference in differences estimates is presented in the form of blue circles increasing in size in line with greater positive differences and as red circles reducing in size with greater negative differences. The P-value is presented as a heat map with green indicating significance and red indicating insignificant results with degrees reflected in changes in shades.

3. Trust a few: Natural disasters and the disruption of trust in Africa

This chapter has been presented as part of the UNU-WIDER PhD Fellows Seminar (2023, Helsinki, Finland)). Feedback and commentary have been included in this thesis.

This chapter was made available as a working paper both for UNU-WIDER and on SSRN (ID 4672385).

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3.1. Introduction

Natural disasters shock societal structures, especially in communities in developing countries characterised with constrained resources and unreliable institutions. Such shocks are likely to influence the social fabric of a community, including the formation of trust in individuals (Dussaillant and Guzmán, 2014; Stephane, 2021).

Trust, as a tenet of social capital, works silently to move communities and institutions forwards towards shared goals and mutual reciprocity (Mattes and Moreno, 2017). It is reliant on the symmetry and reciprocation of mutual interactions (Khodyakov, 2007). Alesina and La Ferrara (2002) observe that one of the strongest factors linked to low levels of trust is a recent account of a traumatic experience. Natural disaster can be regarded as a traumatic experience, especially in developing regions such as those in many places across Africa where they lead to economic vulnerabilities, difficulty in accessing resources and poorly perceived institutional performance (Mackay et al. 2023). These conditions often result in increased competition for resources between groups of individuals (Choi and Bowles, 2007), which, in turn, may contribute to the erosion of interpersonal trust.

In this paper we study whether and how disaster exposure during early adulthood, when individuals arguably go through the most impressionable stages of their lives, affects their trust. Using the 'impressionable years hypothesis' (Sears, 1981; Alwin and Krosnick, 1991; Dinas, 2013; Abdelzadeh and Lundberg, 2016), we test if exposure to disasters during the impressionable years (ages 18–25 years) is negatively associated with trust.

To study the relationship between natural disaster exposure and formation of trust, we merge geocoded disaster data available over the period 1960–2018 from the Geocoded Disasters Dataset (GDIS), with individual-level data from the Afrobarometer social survey conducted over the period 1999–2015. Based on the merged dataset, we are able to calculate the frequency that each individual has been exposed to a disaster over the eight impressionable years (18–25 years) and link it to a broad set of markers of trust in individuals and institutions available in the Afrobarometer. Our dataset covers 88,670 respondents in 36 countries across Africa between 1999 and 2015.

We show that there is a negative association between natural disaster exposure in the impressionable years and generalised trust in people, that is, that most people can be trusted. Similarly, we find that natural disaster exposure also has a negative association with other facets of interpersonal trust, including trust in specific groups of people such as neighbours, people of own nationality, and familiar people. Natural disaster exposure in the impressionable years is also negatively associated with certain dimensions of institutional trust, including trust in the president and the electoral commission. Our results withstand a wide range of checks that demonstrate the robustness of the results to omitted variable bias, definitions of disaster exposure and impressionable years, choices of samples, and estimation approach.

Our research provides several novel contributions to the literature on the impacts of natural disaster exposure on individuals and societies. Primarily, we extend the literature on the relationship between disaster exposure and trust in several important ways. First, studies on the relationship between disasters and trust are inconclusive with regard to the nature of their impact. There is evidence in a number of studies of a positive relationship between disaster occurrences and trust (Toya and Skidmore, 2014; Malesic, 2019; Li et al. 2021; Cisterna et al. 2022) whereas in others the relationship is found to be negative (Albrecht, 2017; Akbar and Aldrich, 2019; Rahman et al. 2020; Lee, 2021). This suggests that the relationship is likely to vary by contextual features, such as institutional quality, disaster response, and the existing social capital in the disaster zone. Moreover, most studies on the impact of disasters on tenants of social capital have been completed at the level of countries or with a focus on distinct contexts (Dussaillant and Guzmán, 2014; Gualtieri et al. 2019; Jovita et al. 2019; Rahman et al.

2020; Cisterna et al. 2022). The evidence from cross-country study design is largely descriptive whereas the studies with specific country focus have limited potential in terms of reconciling the mixed evidence in the literature on the nature of the relationship between natural disaster exposure and trust. By conducting a detailed micro-level study of 88,670 respondents in 36 countries across Africa, we can overcome some of these key limitations in existing studies.

Second, we add to the growing body of literature on the impressionable years hypothesis. The literature has shown that economic or political context or shocks experienced during the period of great mental plasticity in early adulthood have long-term influences on preferences for redistribution (Roth and Wohlfart, 2018), support for democracy (Pyle, 2021), self-censoring (Etchegaray et al. 2019), risk tolerance (Aslam et al. 2021) and confidence in government administration (Chavez, 2018; Aksoy et al. 2020), among others. The evidence on the consequences of exposure to natural disasters in the impressionable years is limited. In particular, Falco and Corbi (2023) use data across countries and within the United States to show that natural disasters experienced in the impressionable years are associated with pro-environmental attitudes. Cross-country studies by Aslam et al. (2021, 2022) on central bankers, on the other hand, show that natural disaster exposure in the impressionable years leads to more conservative behaviours in policymaking. Our paper adds to the emerging work on the exposure to natural disasters, as a specific type of shock, in the impressionable years and is the first to do so in the African context. We provide evidence that the natural disaster exposure in the impressionable years has other crucial consequences on individuals, not covered in existing studies.

Our paper outline is as follows. Section 2 discusses the background relevant to the study in more detail. Section 3 introduces our empirical approach, including the estimation model, data, and variables. Section 4 reports our results. We conclude in Section 5.

3.2. Background

3.2.1. Shocks and trust

Trust as an umbrella term can be viewed as a critical tenant that enables individuals to act cooperatively in the pursuit of shared objectives (Putnam, 2000; Toya and Skidmore, 2014; Mattes and Moreno, 2017). Interpersonal trust considers relational trust between the respondent and other people they may engage with and may be either experiential (subject to external influence) or cultural (a stable intergenerational trait) (Dawson, 2019). Trust is considered to be one of the hallmarks of a cohesive and effective society, reducing the bandwidth taken to make complex sociological decisions (Ward et al. 2014). Fukuyama (1996: 151) argues that it would be 'difficult to conceive' operational modern life without the baselines of societal trust and that trust is critical to social order. Similarly, as it comes to economic exchange, Arrow (1972: 50) points out that 'virtually every commercial transaction has within itself an element of trust'.

Disasters, as a shock, threaten to overload the careful foundations on which trust is formed. Studies on interpersonal trust in response to natural disaster occurrence suggest that there is a clear impact; however, the evidence on the nature of that impact is inconclusive and appears to be situationally dependent. A line of research suggests that natural disasters, by bringing communities together and requiring them to work collaboratively to address challenges, may actually lead to increase in trust (Dussaillant and Guzmán, 2014; Yamamura et al. 2015; Cassar et al. 2017; Ahmad and Younas, 2021; Li et al. 2021; Schilpzand, 2023). Toya and Skidmore (2014: 274) note that despite the measurable human and economic impacts, some of these disasters 'are positively correlated with changes in societal trust'. Similarly, Rayamajhee and Bohara (2021) find that mutual trust between peers is engendered by collective action following a disaster. However, other studies suggest that natural disaster occurrence is corrosive to the sustainability of trust, suggesting that interpersonal trust is a fragile ecosystem of mutually beneficial relations (Albrecht, 2017; Stephane, 2021). Rahman et al. (2020) identifies a reduction in interpersonal trust in individuals exposed to flooding in Bangladesh. Fleming et al.'s (2014) research in Chile, while observing no definitive change in trust levels, finds reduced reciprocity among community members.

Limited evidence from Africa suggests that intra-ethnic and inter-ethnic trust in East African countries is positively affected by droughts (De Juan and Hänze 2021). This relationship, however, wanes with increase in intergroup inequality. Mackay et al.'s (2023) research based on a large sample of African countries suggests that individuals exposed to a disaster are more likely to contact leaders as a group and take part in community meetings—evidence that is consistent with collective action attempts by individuals in the aftermath of a disaster. However, the paper does not consider the changes in trust and neither does it offer insights on whether individuals succeed in acting collectively or whether collective interactions rather lead to conflict and mistrust.

As noted earlier, the influence on trust caused by a natural disaster is situationally dependent (Castillo and Carter, 2011; Carlin et al. 2014; Dussaillant and Guzmán, 2014; Kang and Skidmore, 2018; Bejarano et al. 2021). The pre-existing state of social capital in the affected area is likely to play a role in how much trust depreciates (Dussaillant and Guzmán, 2014). Effective disaster recovery and capable state institutions may further mitigate trust erosion (Carlin et al. 2014; Kang and Skidmore, 2018). Yet, existing research suggests that institutional quality in Sub-Saharan Africa deteriorates after a natural disaster (Khurana et al. 2022, Mackay et al 2023). Even in instances where foreign aid is provided to affected governments, it may be mismanaged by institutions or prevent development of institutional independence and governance (Bräutigam and Knack, 2004). A shock's influence is additionally dependent on the size of that shock, or the level of economic or societal inequality caused by the shock (Castillo and Carter, 2011; Bejarano et al. 2021).

In addition to natural disasters, the literature has considered the impact of other societal shocks (economic, health, political unrest, ecosystem) on social capital and interpersonal trust. Negative macroeconomic shocks have been found to have detrimental effects on interpersonal trust (Iglic, 2014; Jetter and Kristoffersen, 2018; Navarro-Carrillo et al. 2018). While interpersonal trust fell, familial closer relational trust increased (Iglic, 2014; Navarro-Carrillo et al. 2018). Observations in Latin

America on financial recessions find that the more recessions endured, the greater the likelihood that the individual will place trust in their fellow citizens (Searing, 2013).

Health crises may also influence interpersonal trust levels, despite trust itself playing a significant role in individual well-being throughout times of health crisis (Jovanović et al. 2023). During the COVID-19 pandemic, research found marginal increases in interpersonal trust in European countries where the idea of a 'common fate' resulted in a more shared experience (Esaiasson et al. 2020; Ellena et al. 2021). In comparison, Fang et al.'s (2023) study in China finds that exposure to COVID-19 significantly reduced interpersonal trust in the individuals' parents and neighbours.

Political and civil unrest can shake social foundations and disrupt the formation of interpersonal relationships, resulting in lower levels of trust (De Juan and Pierskalla, 2016; Bai and Wu, 2020). Rohner et al.'s (2013) work considers the impact of civil conflict on trust in Uganda using the Afrobarometer survey. The authors find that exposure to conflict decreases trust towards other Ugandans but boosts the respondent's ethnic identity. Nunn and Wantchekon (2011) also report lower trust levels in sub-Saharan Africa among communities that have a history of enslavement.

Environmental crises differ from natural disasters as they are often caused or linked to human activity (Chong and Srebot, 2022). The causal association to human involvement can undermine pillars of social capital, including trust (Gong et al. 2017). Sauri et al. (2003) considers a toxic spill in Spain and find that any increase in interpersonal trust because of the disaster was fleeting and likely a result of the pursuit of shared goals.

3.2.2. Shocks in impressionable years

Research suggests that an individual's impressionable years (between the ages of 18 and 25 years) are a time of great mental malleability and that individuals are highly susceptible to taking on new and lasting ideas, attitudes, and beliefs (Krosnick and Alwin, 1989). Abdelzadeh and Lundberg's (2016) research on trust in Sweden lends credence to the impressionable years hypothesis finding that values of social trust tend to solidify in the years of early adulthood.

Relevant to our research are the studies that use the impressionable years hypothesis to form an empirical hypothesis on how adult outcomes are affected by exposure to shocks during this time. To our knowledge, there are only a few studies on the consequences of exposure to natural disasters in impressionable years. The study by Falco and Corbi (2023) looks at natural disaster exposure in the impressionable years, linking it to pro-environmental attitudes in adulthood. Aslam et al. (2021, 2022) study the policy-making behaviour of central bankers, showing that their exposure to natural disasters in the impressionable years is associated with acting conservatively.

Research on other shocks such as macroeconomic, political, or health (pandemic) shocks, further confirms that the impressionable years are highly susceptible to influence. Negative or adverse macroeconomic conditions within an individual's impressionable years can change individual attitudes, such as preferences for redistribution (Hansen and Stutzer, 2021; Carreri and Teso, 2023) or political party affiliation (Gavresi and Litina, 2023). A study in Argentina conducted by González and Simes (2023) found that individuals exposed to a severe macroeconomic crisis in their impressionable years had notably lower levels of institutional trust and greater perception of corruption. Similar findings for risk taking (Malmendier and Nage,l 2011), career decisions (Oreopoulos et al. 2012), inequality (Roth and Wohlfart, 2018), immigration (McLaren et al. 2021; Laaker, 2023), political attitudes (Ladreit, 2023), and tax morale (Deglaire et al. 2021) show that experiences of macroeconomic instability in impressionable years influence long-term attitudes, and that experiences in these years may therefore provide a baseline for what individuals deem as acceptable.

Research has also been done into political stability and war during an individual's impressionable years. Political repression is suggested to affect an individual's obedience and participation (Etchegaray et al. 2019; Castro Stanley, 2021; Pyle, 2021). Exposure to war or oppression as one comes of age is also shown to reduce trust in government institutions (Chavez, 2018) and political participation (Akbulut-Yuksel et al. 2019) and increase favour in national defence forces (Farzanegan and Gholipour, 2021). Conversely, eras of political irregularity may generate positive political engagement and improved social values (Dinas, 2013; Nteta and Greenlee, 2013). Exposure to pandemics or epidemics throughout the impressionable years also produces observable changes in individual traits such as risk tolerance (Aslam and Farvaque, 2022), scientific trust (Eichengreen et al. 2021), and confidence in political leaders (Aksoy et al. 2020).

3.3. Empirical approach

3.3.1. Data sources and sample

To study the relationship between natural disaster exposure and trust following Equation 1 we create a dataset leveraging the GDIS and Afrobarometer survey, both of which include longitude and latitude information that is used for merging the two datasets. GDIS is built on information from the Emergency Events Database (EM-DAT) and expands upon the initial dataset by including information on the specific location (longitude, latitude) of natural disasters globally between 1960 and 2018 (Rosvold and Buhaug, 2021). GDIS records droughts, floods, storms, mass movement, volcanic activity, extreme temperatures, and wildfires. In Africa, the dataset provides geocoded spatial information on 1,080 different disaster occurrences in 1,565 sub-national locations. In spite of having been relatively recently released, GDIS has been used in a number of studies across disciplines (Friedt and Toner-Rodgers, 2022; Kageyama and Sawada, 2022; Buszta et al. 2023; Lindersson et al. 2023; Mackay et al. 2023; Mester et al. 2023; Schilpzand, 2023; Zeng and Bertsimas, 2023).

We take our individual-level data from the Afrobarometer survey. Afrobarometer is a nationally representative repeated cross-sectional survey conducted in up to 39 countries in Africa since 1999 (Afrobarometer 2023). It provides a comprehensive dataset on a suite of attitudes, preferences, behaviours, and background characteristics. Rounds 1, 3, 4, and 5 of the survey contain several questions about trust that have been leveraged by previous studies on trust (Rohner et al. 2013; De Juan and Hänze, 2021). Our study utilises data from Rounds 1, 3, 4, and 5 (1999–2015) of Afrobarometer covering 36 African countries.[8]

[8] Rounds 2, 6, and 7 do not ask questions on interpersonal trust. Round 8 data were not yet released at the time of conducting this research. Countries include Algeria, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape

Our sample contains 128,594 observations. Table A15 provides a breakdown of observations per country and round for interpersonal trust. We impose several restrictions on the sample. We restrict it to individuals in their post-impressionable years (i.e. aged 26 years or older), dropping 33,449 individuals below the age of 26 years—an approach also taken in other studies (e.g., Roth and Wohlfart, 2018). We further restrict our sample to individuals born after 1942 as GDIS only provides disaster data from 1960 onwards. This results in 6,475 individuals dropped out of the sample. The final dataset used in our research, therefore, provides information on 88,670 individuals exposed to over 1,000 disasters in around 9,500 locations across 36 African countries.[9] Sample sizes used across different regression models vary depending on the number of shared observations across the variables in each model.

3.3.2. Defining disaster exposure

Critical to our approach is linking occurrences of disaster to individual-level data, considering the spatial and temporal dimensions of exposure. In terms of spatial exposure, we consider the disasters occurring within the 30-km radius relative to the individual's PSU location at the first instance. In doing so, we follow the previous research on the impacts of disaster exposure in African context (Mackay et al. 2023); however, we also conduct robustness checks using radii of 10, 20, 40, and 50 km in definition of exposure.

In terms of temporal exposure, we retrospectively assign the disasters that occurred within the 30-km radius of each individual's current location while they were aged 18–25 years. Admittedly, it is possible that individuals may have moved and by following this approach we would be assigning them a disaster that they may have not been in fact exposed to. However, Borderon et al. (2019) suggest that migration in Africa is not directly related to environmental change and is rather a response to socio-

Verde, Cote D'Ivoire, Egypt, Ethiopia, Gabon, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, and Zimbabwe.

[9] Appendix Table A15 indicates the distribution of individuals across rounds and countries for generalised trust and other dimensions of interpersonal trust.

economic contexts. Another study in South Africa (Posel and Casale, 2021) shows that in times of crisis (COVID-19), adults may be inclined to move, but it is more likely to be to the household of a kin or social network within the same or neighbouring community. Nevertheless, acknowledging the possibility of the move across locations, we introduce a robustness check whereby we restrict the sample to individuals under the age of 35 years and assume that their migratory movements would have been more limited since concluding their impressionable years.

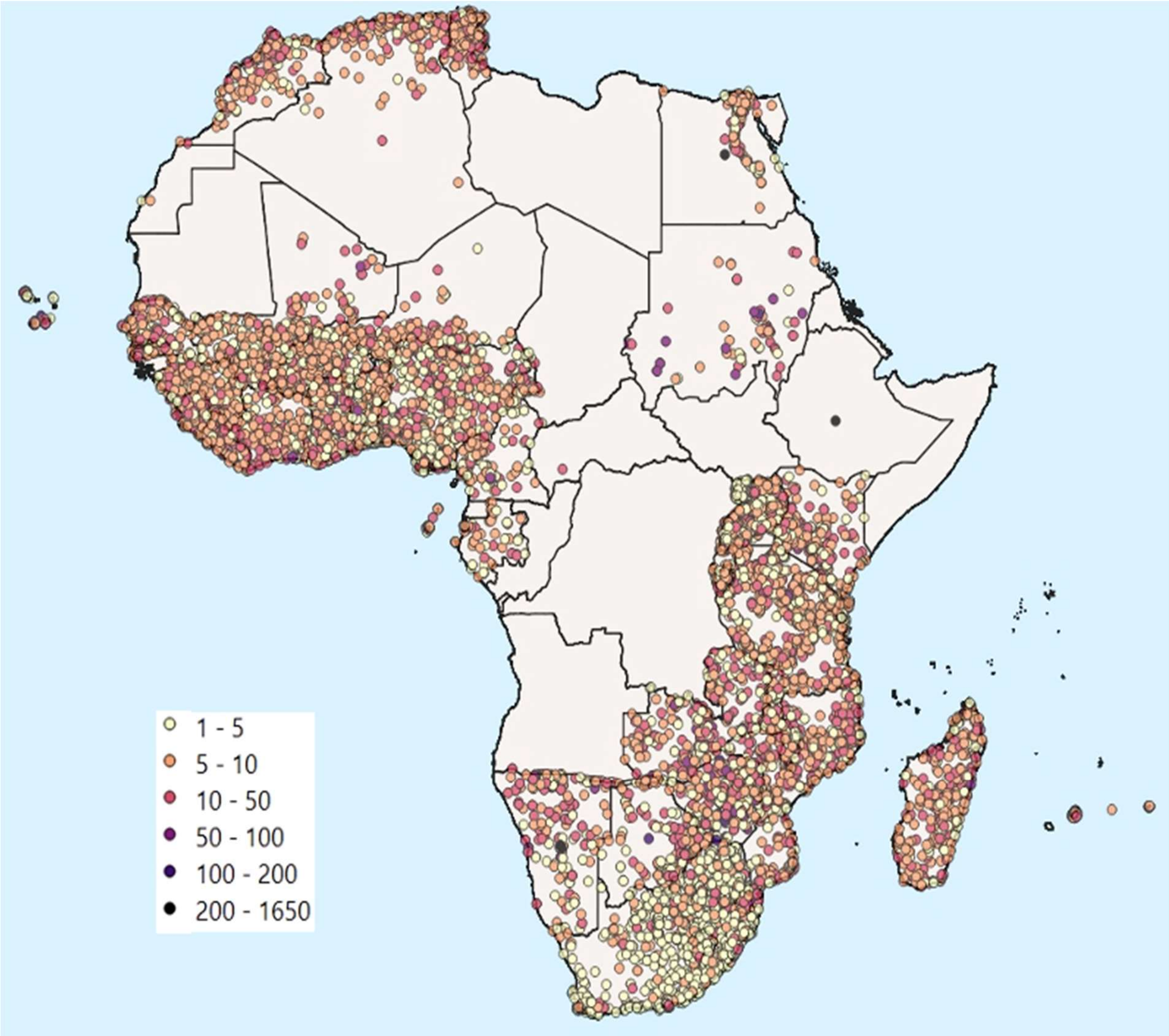
The variable *disaster_frequency* is a count variable that takes values between 0 (no exposure) and 10 (10 or more instances of disaster exposure) corresponding to the number of instances of disaster exposure within the enforced 30-km radius within their impressionable years.[10] The use of this compounded measure of disaster exposure presents an alternative over many existing studies that consider disasters as singular events (Dusaillant and Guzmán, 2014; Akbar and Aldrich, 2017) and offers the opportunity to gain insights into the consequences of intensity rather than an instance of disaster exposure. With natural disasters occurring at an increased frequency over the years (Institute for Economics and Peace, 2020), this is a particularly pertinent aspect of disaster exposure to consider. Figure 2 shows the locations of individuals exposed to disasters throughout their impressionable years.

3.3.3. Defining trust

Following existing studies, we first focus on generalised trust (e.g., Nunn and Wantchekon, 2011; Bai and Wu, 2020). We then expand the set of trust variables to consider additional markers of interpersonal as well as institutional trust in robustness checks. Definitions of the trust variables used across our analysis are presented in Appendix Table A16. Sample means are reported in regression tables, and sample sizes vary by type of trust and the overlap in the number observations across the variables used in each model.

[10] There were 165 individuals exposed to over 10 disasters and subject to the cap. Total exposure frequency is capped at 10 to limit the influence of outliers. We also tested our model without the cap and the results are robust.

Figure 2: Locations of individuals exposed to disasters throughout their impressionable years



Note: Circles indicate the primary sampling units (PSU) in the Afrobarometer. The colour tones (captured in the legend) indicate the number of individuals in that PSU exposed to a disaster during their impressionable years.

Source: authors' creation using Afrobarometer and GDIS data. The map was created using QGIS, an open-source system under the Creative Commons license CC BY-SA.

To measure generalised trust, we use the following Afrobarometer question: *Let's turn to your views on your fellow citizens. Generally speaking, would you say that most people can be trusted or that you must be very careful in dealing with people?* Answers take the values of 0 for 'must be very careful' and 1 for 'most people can be trusted'.

This question, or akin wording, has been extensively used across surveys (e.g., the General Social Survey, World Values Survey) and in the literature looking at generalised trust globally

(Rosenberg, 1956; Fehr et al. 2002; Sturgis and Smith, 2010; Sapienza et al. 2013; Bai and Wu, 2020) as well as in Africa (Nunn and Wantchekon, 2011; Monyake, 2012; Wegenast et al. 2022).

Individuals' interpretations of trust questions may vary depending on whether they consider people in general or only consider individuals known to them (Sturgis and Smith, 2010). To mitigate this issue as well as to form a holistic view of interpersonal trust, we additionally use variables that measure trust in relatives, neighbours, people of the same ethnic group, people of a different ethnic group, people of the same nationality, and other people the individual may know (Nunn and Wantchekon, 2011; Buzasi, 2015; Robinson, 2020; De Juan and Hänze, 2021). These variables are measured on a Likert scale from 0 (no trust at all) to 3 (trusting a lot), and we use the original survey response categories in the analysis. Additionally, mimicking the approach of Adhvaryu and Fenske (2023), we produce an index of interpersonal trust. This index is constructed as the mean of response values on trust questions on which answers are available. For example, if an individual provided responses on three different dimensions of trust (giving responses of 0, 1, 2, and 3 on a Likert scale), we use the mean of their responses as their index (1.667).

In addition to studying the interpersonal dimensions of trust, which is the focus of the current paper, we also look at the institutional dimension of trust. Doing so is important, given that some instances of literature suggest that the evaluations of government performance and perceptions of trust in government fall in response to disaster exposure (Thoresen et al. 2018; Akbar and Aldrich, 2019; Lee, 2021; Mackay et al. 2023). Not only may the deterioration in the quality of institutions post-disaster have implications for trust in institutions, but it may also exacerbate the conditions of despair and competition over scarce resources, that in turn are likely to bring down trust in individuals. Afrobarometer affords the possibility to look at a wide range of markers of institutional trust, including trust in the president, parliament, electoral commission, tax department, local assembly, ruling party, opposition party, police, army, courts, and traditional leaders—all of which have been used in previous studies and record responses of 0, 1, 2, and 3 on a Likert scale (Lavallée et al. 2008; Addai et al. 2011; Hutchison, 2011; Chu and Shen, 2017; Godefroidt et al. 2017; Ishiyama et al. 2018; Dreier and Lake, 2019; Isani and Schlipphak, 2022; Diop and Asongu, 2023; Egger et al. 2023). Additionally, we construct an index of institutional trust following the same approach used to construct our index of interpersonal trust.

3.3.4. Summary statistics

Table 4 provides the summary statistics for all variables based on an extensive model specification (Table 5, model 3). In addition to the basic controls specified in equation (1), namely the dummies for individuals' gender and urban vs. rural status of their residence, this specification includes controls for individuals' socio-economic status including measures of their educational attainment, employment status and living conditions.

Table 4: Summary statistics

	Mean	*Min*	*Max*
Trust (generalised)	0.188	0	1
	(0.391)		
Disaster frequency	0.535	0	10
	(1.420)		
Gender (male)	0.513	0	1
	(0.500)		
Urban	0.372	0	1
	(0.483)		
No or primary education	0.580	0	1
	(0.494)		
Secondary or tertiary education	0.420	0	1
	(0.494)		
Unemployed (not looking)	0.336	0	1
	(0.472)		
Unemployed (looking)	0.257	0	1
	(0.437)		
Employed	0.407	0	1
	(0.491)		
Living conditions (bad or fairly bad)	0.499	0	1
	(0.500)		
Living conditions (neither bad nor good, good or fairly good)	0.501	0	1
	(0.500)		

Note: Summary statistics provided using sample from model 3 of Table 2, sample size: 52,459. Standard deviations are in parentheses. Omitted categories in model 3 of Table 5 include *No or primary education*, *Unemployed (not looking)*, and *Living conditions (neither bad nor good, good or fairly good)*.

In this sample, only 19 per cent of respondents agree that most people can be trusted, indicating an already low baseline level of generalised trust. The average disaster exposure stands at 0.535.

Around 51 per cent of individuals in this sample are males and 37 per cent reside in an urban area with the remaining 63 per cent of individuals coming from rural areas. In terms of educational attainment, less than half of the sample, 42 per cent, have secondary or tertiary attainment with the remainder of the sample having primary or no education. Employed individuals comprise 41 per cent of the sample whereas the remaining are either unemployed but looking for a job (26 per cent) or unemployed and not looking for a job (33 per cent). Half of the respondents in the sample describe their living conditions as bad or fairly bad whereas the remaining half live in neither bad nor good, good or fairly good conditions.

3.3.5. Empirical model

The empirical model to study the relationship between the frequency of exposure to natural disasters during an individual's impressionable years and their reports of trust, is as follows:

$$Y_{ijlt} = \alpha + \beta \, disaster\_frequency_{l,impyears} + \boldsymbol{\gamma} \boldsymbol{X}'_{it} + \delta_l + \theta_t + \varepsilon_{ijlt} \quad (1)$$

where Y_{ijlt} is a binary variable capturing the trust outcome for individual *i* born in year *j* residing in location *l* and interviewed in year *t*. Our primary variable of interest is the frequency of natural disaster exposure during the impressionable years $disaster\_frequency_{l,impyears}$. As control variables, we consider a vector of individual-level variables including gender, year of birth dummies and urban residence dummy (defined within the survey), denoted as $\boldsymbol{X}'_{it}$, sub-national region dummies, δ_l, and year fixed effects (as per the year of the respondents survey), θ_t.[11] ε_{ijlt} denotes idiosyncratic

[11] In additional specifications, we also control for individuals' education, employment, self-reported living conditions, own ethnicity share and religion fixed effects. Whilst risk preference and time preference are shown

error terms. For simplicity, we estimate linear probability models, clustering the standard errors at the round and primary sampling unit (PSU) level identified within Afrobarometer.[12]

3.4. Results

3.4.1. Baseline results

Our baseline model estimates the association between exposures to natural disasters during an individual's impressionable years and the influence this has on the formation of generalised trust. Table 5 presents our results with Model 1 estimating Equation 1, our baseline specification; Model 2 introducing controls for exposure in earlier years to Equation 1; Model 3 adding controls for education, employment, and self-reported living conditions to Equation 1; and Model 4 adding a control for the respondents share of ethnicity in their region and religion fixed effects to Equation 1.

The results of the estimation of our baseline model are reported in Model 1 and suggest a negative association between exposure to disasters in impressionable years and generalised trust with a unit increase in disaster exposure leading to a 0.4-percentage point reduction in trust. Additionally, the insignificant coefficient on the gender dummy suggests that trust does not vary systematically by gender.[13] On the other hand, residents of urban areas are less likely to be trusting relative to their rural counterparts. Our estimates on the year of birth dummies, not shown in Table 5 to conserve space, suggest that age is a significant determinant of trust (the coefficients are jointly significant at 1 per cent).

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to be covariates of trust in some studies (Albanese et al. 2017), disaster shock is likely to have impacts on these preferences (Cassar et al. 2017), and as such, inclusion of these variables in the model would lead to the problem of "bad controls" (Angrist and Pischke, 2009). Information on these variables is also not available in the Afrobarometer.

[12] In robustness checks, we also estimate non-linear models of interpersonal trust.

[13] In robustness checks we additionally explore whether the relationship between natural disaster exposure and trust varies by gender.

Based on the coefficient signs, those born in earlier years exhibit higher propensity to trust relative to those born in later years.

Are the results on the negative relationship between disaster exposure and trust robust to potentially relevant variables currently omitted from the model? First, we ask whether our finding on the negative relationship between disaster exposure and generalised trust is exclusive to the impressionable years or tied to exposure throughout other developmental periods of one's childhood. We test the robustness of the results to controlling for disaster exposure at formative years (ages 0–8 years)[14] and the periods between the formative and impressionable years (ages 9–17 years) in Model 2. The results show that the coefficient on our variable of interest (i.e. disaster exposure in impressionable years) is robust to this change in model specification. Moreover, exposure in earlier periods does not appear to be significantly correlated with generalised trust. This is the case even when omitting the exposure in impressionable years from the regression. This finding strengthens the justification of using the impressionable years rather than other periods of an individual's developmental trajectory as our reference point in this research.

In our baseline model reported in Model 1, we only control for exogenous background characteristics of individuals. In Model 3 of Table 5 we additionally consider the robustness of the results to omitted socio-economic variables including education, employment, and self-reported living conditions (admittedly, some of these may be endogenous to disaster exposure in the impressionable years and hence are excluded from the baseline specification). The results reported in Model 3 of Table 5 show that our central result is not affected by the inclusion of these controls. We also find a negative association between educational attainment and generalised trust, which is consistent with findings in the literature (Frederiksen et al. 2016; Güemes and Herreros, 2019; Wu, 2021). Similarly, compared

[14] Although we have disaster data available for the formative years of individuals in the Afrobarometer, the data quality in Africa was not as comprehensive during the earlier years and as such, some disaster occurrences may be omitted (Rosvold and Buhaug 2021). Individuals may be assigned an exposure value of 0 when they could have been exposed to a disaster that was not documented.

with individuals not in the labour force, employed and unemployed individuals are at a lower likelihood of trusting others.[15] As it comes to subjective perceptions of living conditions, we find that individuals with bad or fairly bad self-reported living conditions are less likely to exhibit trust in people relative to those who are better off (Barone and Mocetti, 2016; Jacobs, 2022).

Although socio-economic conditions often shape interpersonal relations, individual beliefs and values are also tied to cultural background. Individuals who are part of an ethnic or cultural minority may face more societal constraints and be less trusting of others (Nunn and Wantchekon, 2011). In the estimates reported in Model 4 we control for individuals' cultural background, by including the share of the region's population that is of the same ethnicity as the respondent and religious denomination dummies. The results show that the negative association between exposure to natural disasters in the impressionable years and generalised trust is robust to controlling for individuals' cultural background. Moreover, we find that a higher share of own ethnicity in the population is associated with higher levels of generalised trust.

While we demonstrate that our results are robust to inclusion of additional controls in Table 5, we cannot control for all sources of omitted variable bias. As an additional test we follow the approach proposed by Oster (2019) to assess how large the selection on unobservables needs to be, compared with the selection on observables, to explain away the entire estimated effect of disaster frequency presented in Model 1 of Table 5. Formally, we evaluate the bias-adjusted coefficient in Oster (2019) as follows:

$$\beta^* \approx \tilde{\beta} - \delta[\dot{\beta} - \tilde{\beta}]\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}} \qquad (2)$$

where $\dot{\beta}$ and $\dot{R}$ are the coefficient and the R-squared from a regression with the treatment only, $\tilde{\beta}$ and $\tilde{R}$ are the coefficients and the R-squared from a regression with the treatment and the observed controls,

[15] Literature suggests that labour market insecurity has a persistent negative effect on generalised trust, and hence, those outside the labour force are likely more sheltered from such stress (Laurence, 2015; Nguyen, 2017).

δ is the relative importance of observables to unobservables, and R_{max} is the R-squared from a hypothetical regression with observable and unobservable controls. Following Oster (2019), the estimated effect of disaster ranges from $\tilde{\beta}$ to β^* assuming $\delta = 1$ and setting $R_{max} = \min\{1.3\tilde{R}, 1\}$. Table A17 in the Appendix presents our results that show that $\delta > 1$ and $[\tilde{\beta}, \beta^*]$ excludes zero. This provides further support to the robustness of our baseline results presented in Model 1 of Table 5.

Table 5: Disaster exposure and generalised trust: baseline results and robustness to omitted variables

	(1)	*(2)*	*(3)*	*(4)*
Dependent variable	Trust: generalised	Trust: generalised	Trust: generalised	Trust: generalised
	Baseline specification	Controlling for exposure at other life stages	Controlling for socio-economic background	Controlling for cultural background
Disaster frequency	−0.004***	−0.004***	−0.003***	−0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Disaster frequency (formative years: ages 0–8 years)		−0.001		
		(0.002)		
Disaster frequency (youth: ages 9–17 years)		−0.001		
		(0.002)		
Gender (male)	-0.002	-0.002	0.003	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Urban	-0.021***	-0.021***	-0.016***	-0.022***
	(0.004)	(0.004)	(0.004)	(0.005)
Secondary or tertiary education			−0.021***	
			(0.004)	
Unemployed (looking)			−0.019***	
			(0.005)	
Employed			−0.017***	
			(0.005)	
Living conditions (bad or fairly bad)			−0.019***	
			(0.004)	
Share of own ethnicity				0.026***
				(0.010)
Religion fixed effects				Y

Mean of dependent variable	0.189	0.189	0.188	0.190
	(0.391)	(0.391)	(0.391)	(0.392)
Mean of disaster frequency	0.534	0.534	0.535	0.483
	(1.419)	(1.419)	(1.420)	(1.321)
Mean of disaster frequency (formative years: ages 0–8 years)		0.129		
		(0.754)		
Mean of disaster frequency (youth: ages 9–17 years)		0.275		
		(0.969)		
Sample size	52,916	52,916	52,459	45,729
R-squared	0.121	0.121	0.124	0.120

Note: ****p*<0.01, ***p*<0.05, **p*<0.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls year of birth, sub-national region, and year fixed effects. All models are based on Afrobarometer Rounds 3 and 5 as the generalised trust information is not available in other waves of the survey. Model 3 includes additional controls for education, employment, and self-reported living condition dummies. Omitted categories are *No or primary education*, *Unemployed (not looking)*, and *Living conditions (neither bad nor good, good or fairly good)*. Model 4 includes a control for the share of the region's population that is of the same ethnicity as the respondent and religion fixed effects. The definition of the dependent variable is provided in Appendix Table A2.

3.4.2. Disasters and other dimensions of trust

Disaster exposure is negatively associated with generalised trust, but is it also associated with other markers of interpersonal trust? To continue our assessment of the link between disaster exposure and trust, we re-run our baseline model using other dimensions of interpersonal trust as the dependent variable. The OLS results reported in Table 6 show that the negative association between disaster exposure and interpersonal trust holds when looking at other markers of interpersonal trust. An important exception is the positive coefficient of trust in (own) relatives, which despite the insignificance, suggests that trust in an individual's own family is resilient to disaster exposure.

On the other hand, based on the results presented in Table 6, there is a marginally significant reduction in the level of trust in an individual's neighbours (Model 2) when exposed to disasters throughout the impressionable years. Results for ethnic inter-group (Model 3) and intra-group (Model 4) trust also show a negative association with disaster exposure, although only the coefficient in the model of intra-group trust is marginally significant. Trust in people of the same nationality (Model 5) is negatively and significantly affected by disaster exposure, as is the measure for trust in other people the individual may know (Model 6). Finally, we run our baseline model using an index of interpersonal trust constructed following the approach described in Section 3. Namely, our index of interpersonal trust uses the mean of response values to questions on trust in relatives, neighbours, the same ethnicity, other ethnicities, the same nationality, and other people the respondent may know. The results reported in Model 7 of Table 6 confirm our earlier findings and suggest that exposure to natural disasters throughout the impressionable years has a negative association with the interpersonal trust overall, potentially causing disruptions in the formation of both generalised and specialised dimensions of interpersonal trust.

Our analysis of the relationship between disaster exposure and trust is not exclusive to interpersonal trust. We additionally re-estimate our baseline model, using markers of institutional trust. Variables concerning institutional trust were also included in Afrobarometer Rounds 2 and 6 and as such we are able to expand our baseline sample to include these waves in this analysis of institutional trust. The results presented in Table 7 suggest that the negative consequences of natural disaster exposure in the impressionable years are not limited to interpersonal trust. We document marginally significant negative associations between disaster exposure and trust in the president (Model 1) and the electoral commission (Model 3). However, we do not find statistically significant associations in models based on trust in specific authorities such as the parliament, local assembly, ruling party, police, army, or the courts. Similarly, the models that apply trust in the tax department and trust in traditional leaders as dependent variables yield insignificant coefficients on disaster frequency. We do observe a marginally significant positive relationship between disaster exposure and trust in the opposition party, which supports the idea that individuals may hold those currently in power as accountable for disaster effects and recovery (Uslaner, 2016).

3.4.3. Robustness to alternative definitions of disaster exposure

Our baseline measure of disaster exposure is based on a simple count of the disasters that occurred in an individual's impressionable years. However, some of these disasters may have been in the individual's immediate proximity whereas others may have taken place further away. Next, we account for this in our definition of frequency of disaster exposure by re-calculating a weighted frequency measure where the weight is based on an individual's relative distance to the disaster event.[16]

The closer the individual is to the disaster, the higher their weights and higher exposure value. We report the results of re-estimating our baseline model using this distance-weighted measure of disaster exposure in Model 1 of Table A18 of the appendix. The results are the same as before, showing a significant negative association between this (distance-weighted) frequency measure of disaster exposure and generalised trust.

Not only does the distance to disaster matter, but its severity should matter too. Next, we modify the weighted measure of disaster exposure, where instead of using an incidence-based frequency measure of disasters, we use a measure of severity of disasters. Although there are many ways to measure disaster severity (based on economic cost, damage, displacement), following the approach in the literature (Wirasinghe et al. 2013; Caldera et al. 2016; Boustan et al. 2020; Caldera and Wirasinghe, 2022) and based on our own data availability, we use the fatality count as our measure of severity. Effectively, our exposure measure is the relative distance-weighted sum of the fatalities caused by the disasters that occurred throughout an individual's impressionable years. Model 2 in Table A18 provides the results based on this severity-based measure of disaster exposure that shows that our baseline results are reasonably robust to using a fatality count as a basis of our measure of disaster exposure.

Much of our paper focuses on disaster frequency, using a disaster frequency measure that ranges from 0 to 10. But the relationship between the frequency of disaster exposure and trust may not necessarily be linear, and one way to engage with this is to distinguish between individuals with no

[16] The relative distance is the distance from the disaster divided by the enforced exposure radius, that is 30 km.

exposure (omitted), relatively infrequent exposure (1–3 times), and relatively frequent exposure (4+ times). Model 3 of Table A18 presents the results. The coefficient estimates on both infrequent and frequent exposure are negative, suggesting that individuals with exposure to natural disasters in the impressionable years exhibit lower levels of generalised trust than those with no exposure. However, our model estimates indicate marginal statistical significance only for the measure of frequent (4+ times) exposure.

Additionally, as a further validation of our measure of disaster exposure, we conduct two placebo tests. In Model 4 we use a randomised variable (randomly allocating each individual a value between 0 and 10) and the coefficient on this measure is insignificant. Model 5 uses a shuffled variable (reordering the values of our baseline treatment variable at random) and similarly, the estimated coefficient on this measure is insignificant. Based on this analysis, it is unlikely that the estimated coefficients on our disaster frequency measure are picking up the effects of some other things.

We also test the robustness of our results to our definition of spatial exposure, which is based on a 30-km radius from an individual's PSU. In Table A19 of the Appendix we use measures of exposure that are defined at 10-km increments in the 10–50 km range. Across all specifications, we estimate negative coefficients on disaster frequency although only within the radius of 20-30km there is evidence of a highly significant effect of disaster exposure.

In addition to testing the robustness of our results to the spatial dimension of our definition of exposure, we conduct robustness checks where we look at the temporal dimension of our definition. In particular, our definition of impressionable years is based on the ages 18–25 years following the definition in the literature (Nteta and Greenlee, 2013; Etchegaray et al. 2019; Eichengreen et al. 2021; Farzanegan and Gholipour, 2021). Moreover, in Model 2 of Table 2, we have shown that the coefficients on measures of exposure at earlier stages of individuals' lives are insignificant. In Appendix Table A20, we present tests for the robustness of our results to changes in our definition of impressionable years.

Table 6: Disaster exposure and other dimensions of interpersonal trust

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Dependent variables	Trust: relatives	Trust: neighbours	Trust: people of the same ethnicity	Trust: people of a different ethnicity	Trust: people of the same nationality	Trust: other people you know	Interpersonal trust index
Disaster frequency	0.004	−0.006*	−0.014	−0.019*	−0.017**	−0.012***	−0.005**
	(0.003)	(0.003)	(0.011)	(0.011)	(0.008)	(0.003)	(0.002)
Mean of dependent variable	2.370	1.800	1.710	1.413	1.355	1.481	1.842
	(0.893)	(1.800)	(0.988)	(0.988)	(1.016)	(1.006)	(0.795)
Mean of disaster frequency	0.495	0.532	0.278	0.278	0.389	0.541	0.495
	(1.345)	(0.532)	(0.278)	(0.844)	(1.117)	(1.422)	(1.346)
Sample size	72,355	53,811	14,875	14,733	18,290	56,484	72,498
R-squared	0.154	0.205	0.202	0.175	0.158	0.171	0.192

Note: ***p<0.01, **p<0.05, *p<0.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. Model 1 is based on Rounds 3, 4, and 5. Model 2 is based on Rounds 3 and 5. Models 3 and 4 are based on Round 3. Model 5 is based on Round 4. Model 6 is based on Rounds 1, 4, and 5. Model 7 is based on Rounds 1, 3, 4, and 5. The choice of models is related to the presence of questions on specific dimensions of trust in different waves (see Appendix Table A2 for definitions).

Table 7: Disaster exposure and institutional trust

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
Dependent variables	Trust: president	Trust: parliament	Trust: electoral commission	Trust: tax department	Trust: local assembly	Trust: ruling party	Trust: opposition party	Trust: police	Trust: army	Trust: courts	Trust: traditional leaders	Institutional trust index
Disaster frequency	−0.006**	−0.002	−0.007**	0.004	−0.000	−0.004	0.005*	−0.003	−0.003	−0.001	0.001	−0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Mean of dependent variable	1.845	1.623	1.628	1.452	1.537	1.572	1.212	1.580	1.970	1.749	1.923	1.645
	(1.122)	(1.078)	(1.107)	(1.064)	(1.074)	(1.131)	(1.051)	(1.109)	(1.066)	(1.055)	(1.074)	(0.764)
Mean of disaster frequency	0.562	0.583	0.582	0.685	0.562	0.554	0.556	0.577	0.611	0.579	0.598	0.573
	(1.453)	(0.583)	(1.495)	(1.637)	(1.466)	(1.438)	(1.439)	(1.482)	(1.539)	(1.485)	(1.504)	(1.477)
Sample size	107,495	104,245	100,219	69,305	104,631	103,608	102,392	109,584	90,072	106,870	49,634	111,204
R-squared	0.164	0.146	0.143	0.136	0.139	0.157	0.078	0.158	0.175	0.138	0.166	0.195

Note: ****p*<0.01, ***p*<0.05, **p*<0.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. The sample includes Afrobarometer Rounds 1, 2, 3, 4, 5, and 6. Models 1, 3, 8, 10, and 12 are based on Rounds 1, 2, 3, 4, 5, and 6. Models 2, 5, 6, and 7 are based on Rounds 2, 3, 4, 5, and 6. Model 4 is based on Rounds 5 and 6. Model 9 is based on Rounds 1, 2, 3, 5, and 6. Model 11 is based on Rounds 2, 4, and 6. The choice of models is related to the presence of questions on specific dimensions of trust in different waves (see Appendix Table A2 for definitions).

Following the approach of Bai and Wu (2020), we extend our impressionable years age bracket first to the ages of 8–22 years (Model 1) and second to the ages of 23–30 years (Model 2), showing that the results are only marginally significant in Model 1 and insignificant in Model 2.

The reductions in both economic and statistical significance of the results in these specifications compared with our baseline suggest that these extended age brackets dilute the influence of the actual impressionable years of ages 18–25 years. Additionally, instead of looking at the frequency of exposure in the impressionable years, in Model 3 of Appendix Table A20, we look at the frequency of exposure in the 5 years leading up to and including the year of the interview. Model 3 provides the results showing that we retain a negative although only marginally significant coefficient on disaster frequency.

3.4.4. Other robustness checks

Finally, we test the robustness of our results to the choice of the estimation method and sample. Our baseline results are based on estimating a linear model. In Appendix Tables A21 and A22 we present the results based on estimating the non-linear counterparts of the models of interpersonal trust presented in Tables 5 and 6.

Given that our baseline measure of trust, *Trust: generalised*, is a dummy variable, we estimate probit models. The results, presented in Table A21, are qualitatively interchangeable with our linear model estimates from the baseline model presented in Table 5 (column 1). On the other hand, the additional dimensions of interpersonal trust are measured on the Likert scale distinguishing across the trust levels at 0 – not at all, 1 – just a little, 2 – somewhat, and 3 – a lot. We therefore estimate ordered probit models of individual dimensions of interpersonal trust reported in Table A22.[17] By construction, the marginal effect on the lowest outcome (0 - not at all) always has the opposite sign to that of the highest outcome (3 – a lot). Based on these results, disaster exposure is associated with decreases in the probabilities of trusting ‘somewhat’ or ‘a lot’ people of the same nationality, other people one may

[17] The model of trust index is excluded from this table since it is defined based on the mean responses across individual trust categories and is continuous within a range.

know, and to a lesser extent, one's neighbours and people of a different ethnicity. The nature of these results is in line with those based on the linear model estimations in Table 6.

As our model includes an extensive list of sub-national region dummies, we ask whether heterogeneity at the local level affects the results of our baseline model. To assess this we extend our single-level analysis to allow for dependency of trust within regions and examine the extent of between-region variation in trust. In this multilevel analysis, presented in Table A23, the fixed part explanatory variables are those used in our baseline analysis whereas the random part of the model is specified based on the region identifier. In model (1) we have allowed the intercepts to vary across regions. The variance of the intercept is at 2.2 percent and Intra Class Correlation (ICC) suggests that 14 percent of the variability of trust is due to regional variations. In model (2) we also allow the slopes to vary across regions. The variance of the slope is indistinguishable from zero, and the variance of the intercept and ICC remain the same. Overall, we observe non-negligible variability of trust due to regional variations. Nonetheless, our central result on the relationship between disaster frequency and generalised trust remains robust to applying this alternative estimation approach.

Next, we ask whether there is a variation in our results by the characteristics of the respondent. In particular, a body of work suggests that climate events have gendered impacts (Arora-Jonsson, 2011; Eastin, 2018; Hailemariam et al. 2023). Hence, in Table A24 we explore the relationship between disaster frequency and trust in separate sub-samples of male and female individuals (models 1 and 2) as well as by including an interaction term between disaster frequency and gender in the full sample (model 3). In both sub-samples, we estimate negative significant coefficients on disaster exposure. In fact, the coefficient is slightly larger in size in the male sub-sample. We additionally explore the potentially gendered patterns in the relationship between disaster exposure and trust, by augmenting our baseline model with an interaction term of gender and disaster frequency. The coefficient on the interaction term (as well as gender dummy) is statistically insignificant as seen in the results reported in the third column of Table A24. Hence, there is no evidence on gendered patterns in the relationship between disaster exposure and trust based on our results.

When assessing exposure during an individual's impressionable years based on their current location of interview, we need to be aware of the potential for measurement error associated with migration. Rohner et al. (2013) suggest that migration associated with shocks in Africa is likely to be within the regions identified within Afrobarometer and using sub-national region fixed effects, as we do, should offset this risk. Nonetheless, we run an additional robustness check using a specific age sub-sample between 26 and 35 years. Given the recency of impressionable years for this age group, the concerns over migration may be less applicable here than in older age groups. The results reported in Model 1 of Table A25 based on this younger sub-sample are consistent with our baseline result and confirm the negative significant relationship between disaster exposure and trust.

As Figure 2 shows, disasters are prevalent across all countries of our study; however, some countries are affected much more than others. To assess whether our results are driven by countries affected the most by the disasters we follow the approach of Eichengreen et al. (2021) to exclude the five most-affected countries by disaster frequency from the sample. Model 2 of Appendix Table A25 reports our results based on a sub-sample that excludes Kenya, Madagascar, Mozambique, Algeria, and Malawi as the countries with the greatest frequency of disaster according to GDIS.[18] Once again, our results remain robust.

As discussed earlier, disasters and shocks create and further exacerbate existing vulnerabilities in societies, likely inducing heightened competition over resources and possibly conflict. Hence, conflict may be a mechanism in the context of our study, and possibly, the estimates on disaster frequency may be picking up what could be attributed to conflict. However, conflict is an extreme manifestation of tensions in a society, and the link between natural disasters and trust does not necessarily have to be mediated or driven by conflict. To throw light on these issues, we incorporate a measure of conflict exposure in our analysis in the last column of Appendix Table A25. We use the geo-referenced Uppsala conflict dataset between 1989 and 2016, which means we restrict our sample to

[18] In these five countries the mean disaster exposure across the baseline sample is 0.699, whereas in the remaining countries the mean disaster exposure is 0.367.

individuals born after 1971 to be able to construct a measure of conflict exposure in the impressionable years (Sundberg and Melander, 2013; Davies et al. 2023). We follow a similar approach to defining a disaster exposure in constructing our measure of conflict exposure; that is, we take the count of conflicts having occurred within the 30-km radius of an individual's PSU over the course of their impressionable years (i.e. ages 18–25 years).

Given the use of a sub-sample for the purposes of this analysis, first, in Model 3 of Appendix Table A25 we ascertain that our baseline results hold within this sub-sample, and as can be seen, they do. In the final model 4 of Appendix Table A25, we augment the regression with a measure of conflict exposure. Interestingly, the coefficient on this measure, though negative in sign, is statistically insignificant. Moreover, it leaves our central result largely unaffected. Hence, it is unlikely that the relationship between natural disaster exposure and trust is driven by exposure to conflict.

3.5. Conclusion

Shocks experienced throughout one's impressionable years have the potential to influence adult behaviours and attitudes in the long term. By matching data on over 1,000 natural disaster occurrences with individual-level data on 88,670 individuals across 36 African nations, we have shown that exposure to natural disasters during early adulthood is negatively associated with generalised trust. Additionally, individuals exposed to disaster in this period report reduced trust levels in their neighbours, people of own nationality, and other people they may know. Not only do disasters affect interpersonal trust, but they also have negative implications for trust in key political institutions such as the president and the electoral commission. Our results are based on controlling for year of birth and sub-national region dummies and are robust to a battery of robustness checks.

Our results have important implications for the academic and policy discourse in development, and especially in the context of African countries. They suggest that natural disasters, which are likely to intensify amidst climate change, are likely to have profound consequences on societies through their long-term impacts on trust—a societal trait that is crucial for any form of exchange (Arrow 1972). Moreover, with implications for not only interpersonal but also selected dimensions of institutional trust, natural disasters are likely to have a lasting impact on the stability and prosperity of the societies, given the critical role played by institutional trust for government legitimacy and individuals' willingness to support policies including those for sustainable future (Smith and Mayer, 2018; Fairbrother et al. 2019; Bargain and Aminjonov, 2020; Brodeur et al. 2021). Our results, however, are based on data from the African continent, and given the cultural, institutional, and environmental characteristics specific to this part of the world, caution needs to be taken in applying the findings of our work outside of the continent. In particular, effective disaster recovery and capable institutions may mitigate trust erosion, and economic vulnerability, difficulty in accessing resources and poorly perceived institutional performance in many African countries (Mackay et al. 2023) is likely at play in the negative relationship between disaster exposure and trust established in this paper. Adapting and extending our analysis to other parts of the world is an important direction of future research.

3.6. References

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3.7. Appendix

Table A15: Breakdown of observations per country and round for generalised and interpersonal trust

	Afrobarometer round				
Country	**1**	**3**	**4**	**5**	**All**
Algeria	1326	0	0	891	2217
Benin	707	0	851	891	2449
Botswana	774	1602	789	791	3956
Burkina Faso	1430	0	824	932	3186
Burundi	732	0	0	888	1620
Cameroon	2007	0	0	793	2800
Cape Verde	1504	727	802	795	3828
Cote D'Ivoire	653	0	0	912	1565
Egypt	1665	0	0	924	2589
Ethiopia	0	0	0	1650	1650
Gabon	1425	0	0	0	1425
Ghana	815	832	806	1671	4124
Guinea	738	0	0	888	1626
Kenya	0	845	797	1760	3402
Lesotho	0	691	729	796	2216
Liberia	0	0	877	950	1827
Madagascar	0	1027	1056	908	2991
Malawi	0	734	826	1709	3269
Mali	0	882	932	920	2734
Mauritius	0	0	0	1016	1016
Morocco	0	0	0	892	892
Mozambique	0	801	678	1636	3115
Namibia	0	762	774	787	2323
Niger	0	0	0	962	962
Nigeria	0	1283	1406	1602	4291
Senegal	0	835	856	860	2551
Sierra Leone	0	0	0	967	967
South Africa	0	1696	1757	1715	5168
Sudan	0	0	0	810	810
Swaziland	0	0	0	848	848
Tanzania	0	976	900	1879	3755
Togo	0	0	0	803	803
Tunisia	0	0	0	961	961
Uganda	0	1491	1658	1771	4920
Zambia	0	851	817	784	2452
Zimbabwe	0	717	791	1849	3357
Total	**13776**	**16752**	**18926**	**39211**	**88665**

Source: authors' compilation based on Afrobarometer data.

Table A16: Variable definitions

Estimation topic	Variables	Definition	Rounds
Baseline measure of interpersonal trust	Trust: generalised	0-1 binary variable; equals 0 if the individual indicates you must be very careful in dealing with people and equals 1 if the individual indicates that most people can be trusted. We use the original survey response categories.	3, 5
Other measures of interpersonal trust	Trust: relatives	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	3, 4, 5
	Trust: neighbours	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	3, 5
	Trust: people of the same ethnic group	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	3
	Trust: people of a different ethnic group	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	3
	Trust: people of the same nationality	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	4
	Trust: other people you know	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	1, 4, 5
	Interpersonal trust index	Mean of response values on interpersonal trust questions on which answers are available.	1, 3, 4, 5
Measures of institutional trust	Trust: president	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	1, 2, 3, 4, 5, 6
	Trust: parliament	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	2, 3, 4, 5, 6
	Trust: electoral commission	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	1, 2, 3, 4, 5, 6

	Trust: tax department	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	5, 6
	Trust: local assembly	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	2, 3, 4, 5, 6
	Trust: ruling party	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	2, 3, 4, 5, 6
	Trust: opposition party	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	2, 3, 4, 5, 6
	Trust: police	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	1, 2, 3, 4, 5, 6
	Trust: army	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	1, 2, 3, 5, 6
	Trust: courts	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	1, 2, 3, 4, 5, 6
	Trust: traditional leaders	0-3 variable; equals 0 if the individual indicates they do not trust the entity at all, 1 if the individual indicates they trust the entity just a little, 2 if they trust them somewhat, 3 if they trust them a lot. We use the original survey response categories.	2, 4, 6
	Institutional trust index	Mean of response values on institutional trust questions on which answers are available.	1, 2, 3, 4, 5, 6

Source: authors' compilation based on Afrobarometer data and codebook.

Table A17: Oster test for omitted variable bias

	Proportionality		Identified set	
	$\delta_{R_{max}=\min\{1.3\tilde{R},1\}}$	$\|\delta\| > 1$	$[\tilde{\beta}, \beta^*_{(R_{max}=\min\{1.3\tilde{R},1\},\delta=1)}]$	Excludes 0?
	2.266	Yes	[−0.002, −0.004]	Yes
Baseline controls		Yes		
Sample size		52,916		

Note: the dependent variable is trust: generalised. δ indicates the value of selection of unobservables to observables assuming the maximum value of R-squared is R_{max}. Coefficient bounds are calculated assuming $\delta = 1$ and $\delta R_{max} = \min\{1.3R, 1\}$.

Table A18: Disaster exposure and generalised trust: alternative measures of exposure

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Dependent variables	Trust: generalised	Trust: generalised	Trust: generalised	Trust: generalised	Trust: generalised
Disaster frequency, distance-weighted	−0.006***				
	(0.002)				
Disaster severity, distance-weighted		−0.002**			
		(0.001)			
Disaster frequency dummy (1–3)			−0.001		
			(0.005)		
Disaster frequency dummy (4+)			−0.020**		
			(0.009)		
Disaster placebo (randomised)				0.001	
				(0.001)	
Disaster placebo (shuffled)					−0.001
					(0.001)
Mean of dependent variable	0.189	0.189	0.189	0.189	0.189
	(0.391)	(0.391)	(0.391)	(0.391)	(0.391)
Mean of disaster frequency, distance-weighted	0.293				
	(0.003)				
Mean of disaster severity, distance-weighted		0.194			
		(2.019)			
Mean of disaster frequency dummy (1–3)			0.177		
			(0.382)		
Mean of disaster frequency dummy (4+)			0.043		
			(0.204)		
Mean of disaster placebo (randomised)				5.001	
				(2.894)	
Mean of disaster placebo (shuffled)					0.488
					(1.366)
Sample size	52,916	52,916	52,916	52,916	52,916
R-squared	0.122	0.121	0.121	0.121	0.121

Note: ***p<0.01, **p<0.05, *p<0.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. Models are based on Afrobarometer Rounds 3 and 5 since the generalised trust information is not available in other waves of the survey. Disaster frequency, distance-weighted (Model 1), calculates exposure using a weighted measure of disaster frequency where the weight is the relative distance to the recorded epicentre of the disaster divided by the exposure radius (i.e. 30 km). Disaster severity, distance-weighted (Model 2), presents the relative distance-weighted sum of the fatalities caused by the disasters. Omitted category in Model 3 is 'not exposed to disaster'. Model 4 randomly assigns individuals a disaster exposure value between 0 and 10 as a randomization placebo test. Model 5 randomly shuffles existing disaster exposure values as a shuffled placebo test.

Table A19: Disaster exposure and generalised trust: exposure defined at 10, 20, 30, 40, 50-km radii

	(1)	*(2)*	*(3)*	*(4)*	*(5)*
Exposure radius:	10 km	20 km	30 km	40 km	50 km
Dependent variable:			Trust: generalised		
Disaster frequency	−0.001	−0.004***	−0.004***	−0.002*	−0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Mean of dependent variable	0.189	0.189	0.189	0.189	0.189
	(0.391)	(0.391)	(0.391)	(0.391)	(0.391)
Mean of disaster frequency	0.158	0.339	0.534	0.754	1.039
	(0.662)	(1.050)	(1.419)	(1.764)	(2.123)
Sample size	52,916	52,916	52,916	52,916	52,916
R-squared	0.121	0.121	0.121	0.121	0.121

Note: ***p<0.01, **p<0.05, *p<0.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. Models 1–5 are based on Afrobarometer rounds 3 and 5 since the generalised trust information is not available in other waves of the survey.

Table A20: Disaster exposure and generalised trust: alternative definitions of exposure—additional tests

	(1)	(2)	(3)
Dependent variables	Trust: generalised	Trust: generalised	Trust: generalised
Disaster frequency (ages 8 – 22)	-0.002*		
	(0.001)		
Disaster frequency (ages 23 – 30)		-0.002	
		(0.001)	
Disaster frequency (past 5 years)			-0.003*
			(0.002)
Mean of dependent variable	0.187	0.189	0.189
	(0.390)	(0.391)	(0.391)
Mean of disaster frequency	0.638	0.741	0.783
	(1.596)	(1.806)	(1.583)
Sample size	48,290	52,415	52,916
R-squared	0.122	0.122	0.121

Note: *** p <.01, **p <.05, * p <.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. All models are based on Afrobarometer rounds 3 and 5 since the generalised trust information is not available in other waves of the survey.

Table A21: Disaster exposure and generalised trust: probit model estimates

	(1)	(2)
	Probit coefficient	Probit marginal effect
Dependent variables	Trust: generalised	Trust: generalised
Disaster frequency	-0.018***	-0.004***
	(0.006)	(0.001)
Sample size	52,551	
Pseudo R2	0.116	

Note: *** p <.01, **p <.05, * p <.1. Probit coefficients (column 1), marginal effects (column 2) and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. All models are based on Afrobarometer rounds 3 and 5 since the generalised trust information is not available in other waves of the survey.

Table A22: Disaster exposure and other dimensions of interpersonal trust: ordered probit model estimates

Variable	(1)	(2)	*(3)*	*(4)*
	Levels of trust			
	0 (not at all)	1 (just a little)	2 (somewhat)	3 (a lot)
Dependent variable:	Trust: relatives			
Disaster frequency	-0.001	-0.001	-0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Pseudo r-squared	0.083			
Sample	72,355			
Dependent variable:	Trust: neighbours			
Disaster frequency	0.001*	0.002*	-0.001*	-0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Pseudo r-squared	0.088			
Sample	53,811			
Dependent variable:	Trust: people of the same ethnicity			
Disaster frequency	0.003	0.004	-0.001	-0.005
	(0.002)	(0.003)	(0.001)	(0.004)
Pseudo r-squared	0.085			
Sample	14,875			
Dependent variable:	Trust: people of a different ethnicity			
Disaster frequency	0.006*	0.003*	-0.004*	-0.005*
	(0.003)	(0.002)	(0.002)	(0.003)
Pseudo r-squared	0.072			
Sample	14,733			
Dependent variable:	Trust: people of the same nationality			
Disaster frequency	0.006**	0.002**	-0.003**	-0.004**
	(0.003)	(0.001)	(0.002)	(0.002)
Pseudo r-squared	0.063			
Sample	18,290			
Dependent variable:	Trust: other people you know			
Disaster frequency	0.004***	0.002***	-0.002***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Pseudo r-squared	0.069			
Sample	56,484			

Note: *** p <.01, **p <.05, * p <.1. Ordered probit marginal effects and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. *Trust: relatives* is based on Rounds 3, 4, and 5. *Trust: neighbours* is based on Rounds 3 and 5. *Trust: people of the same ethnicity* and *Trust: people of a different ethnicity* are based on Round 3. *Trust: people of the same nationality* is based on Round 4. *Trust: other people you know* is based on Rounds 1, 4, and 5.

Table A23: Multilevel analysis

	(1)	(2)
Dependent variables	Trust: generalised	Trust: generalised
Disaster frequency	-0.003**	-0.003**
	(0.001)	(0.001)
Residuals variance	0.136	0.136
Intercept variance	0.022	0.022
Slope variance		0.000
ICC	0.141	0.142
Sample size	52,916	52,916
Log likelihood	-23019.47	-23019.47

Note: *** p <.01, **p <.05, * p <.1. Standard errors are in parentheses. The fixed part variables are those used in the baseline analysis (gender, urban dummy, year of birth and year fixed effects) while the random part of the model is specified based on the region identifier. Model 1 allows the intercepts to vary across regions. Model 2 also allows the slopes to vary across regions.

Table A24: Disaster exposure and generalised trust: gender-based heterogeneities

	(1)	(2)	(3)
Sub-sample:	Females	Males	All
Dependent variables	Trust: generalised	Trust: generalised	Trust: generalised
Disaster frequency	-0.003*	-0.005***	-0.004***
	(0.002)	(0.002)	(0.002)
Gender			-0.003
			(0.004)
Disaster frequency* Gender			-0.001
			(0.002)
Mean of dep variable	0.188	0.190	0.189
	(0.391)	(0.392)	(0.391)
Mean of disaster frequency	0.555	0.513	0.534
	(1.433)	(1.404)	(1.419)
Sample size	25,801	27,115	52,916
R-squared	0.141	0.125	0.121

Note: *** p <.01, **p <.05, * p <.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls urban status, year of birth, sub-national region, and year fixed effects. All models are based on Afrobarometer rounds 3 and 5 since the generalised trust information is not available in other waves of the survey.

Table A25: Disaster exposure and generalised trust: other sub-samples

	(1)	(2)	(3)	(4)
Sub-sample:	26–35 years old	Without five most exposed countries	Born after 1970	Born after 1970
Dependent variables	Trust: generalised	Trust: generalised	Trust: generalised	Trust: generalised
Disaster frequency	-0.006***	-0.004**	-0.004***	-0.004**
	(0.02)	(0.001)	(0.002)	(0.002)
Conflict frequency				-0.001
				0.001
Mean of dep variable	0.175	0.190	0.180	0.180
	(0.380)	(0.393)	(0.384)	(0.384)
Mean of disaster frequency	0.933	0.462	0.816	0.816
	(1.812)	(1.286)	(1.680)	(1.680)
Mean of conflict frequency				1.093
				(2.876)
Sample size	22,311	43,286	28,266	28,266
R-squared	0.131	0.126	0.124	0.124

Note: *** p <.01, **p <.05, * p <.1. OLS coefficients and standard errors, clustered at the PSU and survey wave level, in parentheses, are reported. All regressions include baseline controls gender, urban status, year of birth, sub-national region, and year fixed effects. All models are based on Afrobarometer rounds 3 and 5 since the generalised trust information is not available in other waves of the survey. Model 1 is restricted to 26–35 years old given the recency of impressionable years to mitigate the measurement error due to migration. Model 2 is based on a sub-sample without the five most disaster-exposed countries (Kenya, Madagascar, Mozambique, Algeria, and Malawi). Models 3 and 4 are based on a sub-sample of individuals born after 1970. Conflict exposure is calculated as a frequency count throughout the impressionable years in the 30km radius of individual's PSU.

4. Crimes of the current: Natural disasters and crime in Kenya

This chapter is currently under review at World Development.

4.1. Introduction

Natural disasters increase societal vulnerabilities, often forcing individuals into a state of survivalism. The chaos and disorder caused by a disaster also provide opportunities for anti-social behaviours, such as crime. With disruptions in institutional support and economic and societal networks, individuals compete for resources through any means (Lanzafame, 2014). Yet, such situations also have the power to induce pro-social behaviours (Siegel et al. 1999; Van Brown, 2019) and propensity to act collectively to address the challenges in a post-disaster context (Mackay et al 2023). Indeed, the empirical evidence on the relationship between natural disaster exposure and crime is mixed, with studies showing a positive relationship in some cases (Zahran et al. 2009; Herber, 2014; Breetzke and Andresen, 2018), and a negative relationship in others (Kwanga et al. 2017; Silva, 2018; Purnama et al. 2020; Gaherity and Birch, 2022). Often, these are context-specific findings and largely limited to developed country settings (Lemieux, 2014; Frailing et al. 2015; Prelog, 2016; Berrebi et al. 2021) where institutional configurations mitigate the impacts of shocks to an extent.

In this paper we revisit the relationship between natural disaster exposure and crime, focusing on the case of Kenya, a country where both natural disasters and crime are pervasive (Huho et al. 2016; Republic of Kenya, 2021; wa Teresia, 2021; Baraka, 2023). We adopt a mixed methods approach, combining an analysis of a large quantitative dataset with primary qualitative data, to study the relationship between natural disaster exposure and crime, and throw insights on the transmission mechanisms. Individuals and institutions are already made vulnerable by disaster shocks and the additional strain of escalating crime rates is likely to foster chaos and lawlessness. This research approach is thus novel to the literature as it contributes crucial knowledge on the relationship including nuanced understanding on the motives behind criminal behaviours induced by a disaster.

Our quantitative analysis is based on matching the geo-coded data from the Kenyan Afrobarometer survey with the Geocoded Disasters Dataset (GDIS) and geographically mapping exposure to individuals within 50km of their primary sampling unit either pre or post interview. Simply regressing crime on disaster exposure would likely lead to biased estimates as individuals residing in disaster prone areas are likely different to those in non-disaster areas in ways that are relevant to crime. Therefore, we use a cross-sectional difference-in-differences approach, drawing comparisons between individuals who were exposed to a disaster before interview and after interview (at risk of exposure). Using this strategy, we find that natural disasters result in increases in the incidence of crime, with individuals that have been exposed to disaster much more likely to have experienced theft or physical assault, and to fear crime in their home, compared to yet-to-be-exposed individuals.

We complement this analysis with a discussion on the mechanisms motivating crime using primary data collected across 75 semi-structured interviews by the authors in Baringo, Kenya where individuals were severely impacted by the 2020 East Valley Rift flooding. 98 per cent of individuals report an increase in at least one type of crime post-flooding. On one hand, following the intuitions in Becker (1968), Sah (1991) and Freeman (1999), we analyse the individuals' perceptions on whether a natural disaster exposure alters the benefits and/or costs of committing a crime. On the other hand, in line with theories of expressive violence (Feshbach 1964; Salfati and Canter, 1999; Salfati, 2000; Cohn and Rotton, 2003; Miethe and Regoeczi, 2004; Thijssen and de Ruiter, 2011), we explore whether, based on individuals' perceptions, crime serves as a vehicle to relieve the stress caused by exposure to a natural disaster or simply is an outcome of poorer self-control due to stress. The interview responses are in line with both scenarios, highlighting the complexity of factors in inducing crime in post-disaster settings.

Our research contributes to the literature on disasters and crime in significant ways. One stream of the literature shows that disaster occurrence reduces crime due to increased altruism and social capital (Zahran et al. 2009; Herber, 2014; Lentini et al. 2016; Hombrados, 2020; Berrebi et al. 2021). Alternatively, another stream suggests crime may increase driven by changes to an individual's opportunity cost, motivating them to participate in crime (Curtis and Mills, 2011; Frailing et al. 2015; Prelog, 2016; Kwanga et al. 2017). Our work, by contributing a case study in a novel context, extends further support to the latter group of studies. Moreover, our analysis of primary data enables us to add nuanced insights on the transmission mechanisms.

Our work also contributes to the literature on the impacts of natural disasters on crime in developing country contexts. In Africa, the effects of disasters are exacerbated by poverty, population growth and institutional failures to change (Khandlhela and May, 2006; Yameogo, et al. 2018; Hallegatte et al. 2020). African economies are also highly vulnerable to weather shocks with climate disasters worsening poverty and leading to additional societal pressures, often culminating in conflict (Lanzafame, 2014; Detges, 2017; Linke et al. 2018; Adler, 2019; Kassegn and Endris, 2021; Shimada, 2022). The focus of the literature on natural disasters in the African context is often on agriculture and livelihoods (Maddison, 2007; Butler and Gates, 2012; Bunei et al. 2013; Yameogo et al. 2018). Studies focusing on Kenya have engaged with issues of pastoralist conflict (Hendrickson et al. 1998; Berger, 2003; Lind, 2003; Omolo, 2010; Adano et al. 2012; Bunei et al. 2013; Sharamo, 2014; Gartner, 2015; Bunei and Barasa, 2017), environmental and/or resource conflict (Bond, 2014; Ide et al. 2014; Waikenda, 2017), and ethnic conflict (Bollig, 1993; Nganga, 2012; Kiprop-Marakis et al. 2019).

Our paper proceeds as follows: section 2 provides background on the literature on natural disasters and crime and discusses the Kenyan context in more detail. Section 3 provides analysis of the relationship between disasters and crime using data from the Kenyan Afrobarometer survey and GDIS, while section 4 provides analysis of the relationship between disasters and crime and the transmission mechanisms using our primary data. Section 5 concludes.

4.2. Background

4.2.1. Natural disasters and crime

Natural disaster occurrence strains social resources and support systems leaving individuals vulnerable and susceptible to behavioural change (Agnew, 2012). Bignon et al. (2017) suggest that shocks, such as a disaster, may alter an individual's opportunity cost of participating in a crime. Disasters are not the only shocks that may impact crime; other shocks such as economic shocks, adverse life events, and health shocks are also shown to alter behaviours and opportunity costs for individuals, creating trickle on effects for crime (Corman et al. 2011; Dix-Carneiro et al. 2018; Corvalan and Pazzona, 2019;

Hodgkinson and Andresen, 2020; Zhang, 2020). The evidence on whether such shocks lead to negative or positive effects on the incidence of crime remains mixed.

The nature of the existing findings on the relationship between natural disaster exposure and crime appears to be dependent on the context-specific circumstances, disaster recovery and institutional support throughout the shock. Studies in the U.S. (Zahran et al. 2009; Berrebi et al. 2021) and New Zealand (Breetzke and Andresen, 2018) suggest that disaster-affected individuals are more likely to lean towards prosocial behaviours and altruism (Siegel et al. 1999). Compounding vulnerabilities in collectivist societies may lend themselves to communal action and prosocial behaviours that view the disaster as a 'consensus situation' (Van Brown, 2019). Research also links reductions in crime post-disaster with effective institutional planning and response. Existing evidence highlights the role of crime prevention campaigns and social capital in Japan 2011 (Herber, 2014), effective public intervention (Lemieux, 2014) and stronger social cohesion during the 2004 Indian Ocean Tsunami (Lentini et al. 2016). However, not all decreases in observed crime may suggest positive developments, as whilst some types of crime decrease, others may increase (Bignon et al. 2017) or simply relocate to non-affected areas where crime is more lucrative (Zahnow et al. 2017).

There is also evidence of an increase in crime following a natural disaster. Prelog (2016) finds higher crime associated with disasters of larger magnitude in the US, highlighting the rise of disaster context in explaining the finding. Disasters may provide the ideal distraction for criminals to take advantage of the panic to enrich themselves (Ogunro et al. 2022). Looking at the aftermath of Hurricane Katrina, increases in crime have been attributed to increased crime opportunities (Curtis and Mills, 2011), abuses in disaster relief (Frailing and Harper, 2007), and pre-existing criminal conditions exacerbated by the disaster (Frailing et al. 2015). Similarly, evacuation orders may make vacant residences ideal for burglaries, as was the case in Texas (Leitner and Helbich, 2011). Based on the literature, changes in weather conditions may also lead to increases in crime; as overall temperatures increase (leading to temperature-aggression and thus expressive violence), so too will the incidence of crime (Ranson, 2014; Blakeslee and Fishman, 2018; Churchill et al. 2023; Wright and Stewart, 2024).

Another strand of literature questions the validity of the observations on disaster-induced crime with reference to the role of media. Studies in this literature suggest that reports of looting, crime and chaos are often exaggerated and perpetuated by the media (Tierney et al. 2006). Nogami (2015, 2018) attributes the media and internet consumption with exacerbating the "myth" of increased crime following a disaster. Nobo and Pfeffer (2012) also touch on media dramatization of crime suggesting that despite increases in looting in New Orleans, much of it was for basic resources undersupplied by the U.S. Government resulting in necessity-driven crime. Using a discussion on social disorganisation, Varano et al. (2010) find only modest increases in crime among the displaced Katrina diaspora, again overdramatised by media reports.

The literature on the influence of disasters on crime in developing countries is still emerging. Observations in Chile suggest conflicting results with earthquakes reducing property crime (Hombrados, 2020) and improving social cohesion (Calo-Blanco et al. 2017), tsunamis stimulating criminality driven by local inequalities (Gaherity and Birch, 2022), and megafires substantially increasing domestic violence (Silva, 2018). In other developing countries, escalation of crime among displaced disaster-victims in Pakistan was not found to be widespread and dependent on the capacity of the responding cities (Siddiqui, 2023). Observations in Indonesia found increases in larceny during and post-disaster spurring calls for government to introduce preventative measures (Purnama et al. 2020). Temperature shocks in Jamaica resulted in increases in violent crimes, yet increased rainfall decreased property crimes (Wright and Stewart, 2024). Lastly, studies on flooding in Nigeria observed that household vulnerability to crime increased during the disaster and so did the incidence of crime, however that increase tapered off quickly afterwards (Kwanga et al. 2017; Shabu and Mbanengen, 2018; Onah et al. 2021).

4.2.2. Kenyan context

While the issue of natural disasters and crime studied in this paper is relevant to most of Sub-Saharan Africa, in this paper we use Kenya as a case study. Kenya provides a highly relevant context to study crime. Over the period from 2014 to 2020, crime levels are estimated to have gone up by 41 per cent (from 69,736 offences in 2014 to 98,408 offences in 2020) [wa Teresia, 2021]. This increase in crime can, in part, be attributed to an inequity of resources and ethnic rivalry, frictions often worsened by the disaster context (wa Teresia, 2021). The 2021 Kenya National Police Service Annual Report on crime identifies the Rift Valley region (the location of our fieldwork) as experiencing the highest crime rates in 2021 with 18,848 reported cases showing an increase of 19 per cent (3,025 cases) compared to the 15,823 cases over the same period in 2020 (Republic of Kenya, 2021).

Natural disasters remain quite prevalent in Kenya, with over 70 per cent of disasters stemming from hydro-meteorological causes (flood and drought) and affecting the livelihoods of millions residing in pastoral districts (Suda, 2000; Huho et al. 2016). Based on GDIS, from the 52 African countries there is disaster data on, Kenya has recorded the highest number of disasters at a total of 412 over the period from 1979 and 2018 (see Appendix Figure A7). The next highest cases are recorded in Madagascar and Mozambique with 369 and 354 total disasters over the same period, respectively. Of the 412 disasters recorded for Kenya in GDIS, 67 per cent are floods.

Environmentally, the Baringo/Rift Valley region provides an ideal case study as although it provides critical access to water and agricultural essentials, it is also often subject to groundwater movement due to plate tectonics. A combination of underground permeability (subterranean outflow) and record rainfall in the 2019 and 2020 seasons caused Lake Baringo to rise to its highest level in decades (Avery, 2020; Cherono, 2021). Lake Baringo itself has more than doubled its size in a decade swelling from 128 square kilometres in 2010 to 268 square kilometres in 2020 (Macharia, 2021). Flood modelling for the Perkerra catchment area (Baringo County, Kenya) observes flood events twice every year with a high flow rate return period of five years suggesting another major flood occurrence in 2025 (Chebii et al. 2022).

Individuals living in the Lake Victoria Basin and Rift Valley region are particularly vulnerable to the effects of floods, symptomatic of their circumstances where poverty forces people to reside in flood-prone areas and cultural attachment to the land results in an unwillingness to move (Opere and Ogallo, 2006). The 2020 and previous floodings at Lake Baringo and the broader Rift Valley has sorely impacted many people, removing them from their homes, livelihoods, agricultural lands, and economic chains (Obando et al. 2016; Muia et al. 2021; Baraka, 2022; Kangogo, 2022). It is estimated that the floods have impacted nearly 400,000 individuals (Baraka, 2023). Impacted individuals have not received any assistance and the Baringo county disaster department is underfunded and unable to cater to the emergency, with individuals in some communities filing a lawsuit against the county government of Baringo (Kangogo, 2022; Baraka, 2023). Many of the residences/structures in the region are not able to withstand floodwaters and residents do not have appropriate materials to mitigate flooding (Victor et al. 2023).

4.3. Natural disasters and crime: Evidence based on Kenyan Afrobarometer survey

The first part of our analysis uses data from the Kenyan Afrobarometer survey, merged with data from GDIS to study the link between disaster exposure and crime.

4.3.1. Empirical strategy

Individuals in disaster-prone areas might be different to those living further away in ways that correlate with crime and the associated perceptions. Therefore, simply regressing crime on disaster exposure is unlikely to lead to reliable estimates on the relationship. To address this identification challenge, we adopt a difference-in-differences approach drawing comparisons between individuals exposed to a disaster before vs. after the survey. This cross-sectional difference-in-differences approach has been used in other contexts, see e.g. Knutsen et al. (2017), Isaksson and Kotsadam (2018), Chung and Rhee (2022), and Mackay et al. (2023).

The identification is based on exploiting the spatial and temporal distances to disaster events, utilising information on individuals' location and interview dates. The literature provides no consensus on what an optimal spatial distance to calculate an individual's exposure based on their location may be. Previous studies employing similar spatial-temporal estimation strategies have employed cut-offs between 25-50km (Knutsen et al. 2017; Isaksson and Kotsadam, 2018; Chung and Rhee, 2022; Mavisakalyan and Minasyan, 2022; Mackay et al. 2023). As a baseline approach, we utilise a 50km radius to define spatial exposure but consider alternative distance cutoffs to define spatial exposure in robustness checks. Similarly, there is no guidance, based on the literature, on the optimal temporal cut-off to define an individual's exposure to a disaster. Following (Mackay et al. 2023), we use 15 years to define temporal exposure in the baseline analysis.[19] Hence, to determine whether an exposure to a disaster took place before or after the interview, we take the earliest disaster within the 50km cut-off in the 15 years before or after the interview date and subtract the interview date. We consider three groups: (a) individuals exposed to a disaster within 50km before interview, (b) individuals exposed to a disaster within 50km after interview, and (c) individuals not exposed to a disaster. Our baseline estimation model is presented as follows:

$$Crime_{ilt} = \alpha_1 exposed50\_before_{it} + \alpha_2 exposed50\_after_{it} + \boldsymbol{\gamma X'_{it}} + \delta_l + \theta_t + \varepsilon_{ilt} \quad (1)$$

where the outcome of interest is $Crime_{ilt}$ for an individual i residing in location l and interviewed in year t. $exposed50\_before_{it}$ and $exposed50\_after_{it,}$ denote exposure to disaster before and after the survey, using 15 years as the reference period as discussed above. The regressions include individual-level controls $\boldsymbol{X}_{it}$ including age, age-squared, gender and urban residence dummy, and dummies for sub-national region δ_l and year of interview θ_t. Our interest in this study is in the differences in the parameters of $exposed50\_before_{it}$ and $exposed50\_after_{it,}$, i.e. α_1-α_2. That is, we are drawing

[19] As we consider a broad temporal exposure period (15-years), one might question whether migration as a result of a disaster may impact the accuracy of our exposure variable. Borderon et al. (2019) suggests that migratory movement within Africa is rarely associated environmental events and instead a response to ongoing socio-economic strife. Similarly, studies have shown that when individuals in Africa do migrate, it is generally within the same family or social network within their current or neighbouring communities (Posel and Casale, 2021). Despite this, and acknowledging the potential for migration, we conduct robustness checks with 10- and 5-year periods used to define temporal exposure to reduce the period available for migration.

comparisons between post-treatment and control individuals on one hand, and pre-treatment and control individuals on the other hand, which provides the difference-in-differences estimator[20].

4.3.2. Data sources and sample

Our analysis combines two sources of data. We use the GDIS, which provides data on the years, specific locations (longitude and latitude), and types of natural disasters between 1960 – 2018 (Rosvold and Buhaug, 2021). GDIS is based on the Emergency Events Database (EM-DAT), which provides information on droughts, floods, storms, mass movement, volcanic activity, extreme temperatures, and wildfires at global scale (EM-DAT, 2023). An event is classified as a disaster when at least one of the following holds: 10 or more human deaths, 100 or more affected people, declaration of a state of emergency, or a call for international assistance (EM-DAT, 2023). Droughts are not included in our modelling as due to their slow onset, exact identification of start dates – an essential piece of information in our estimation approach - is improbable (EM-DAT merely records the month of commencement). GDIS reports 412 disasters occurred across 81 locations in Kenya (some disasters are recorded across multiple locations if their scope is large enough). Of these 412 disasters, 276 are floods.

Our individual-level data is taken from the Afrobarometer, a nationally representative repeated cross-sectional survey of up to 39 countries in Africa since 1999. Our study utilises the Kenyan survey in rounds 2 – 6 (2003 – 2014), comprising a total of 9,576 respondents in the raw sample[21]. The Afrobarometer dataset contains a suite of crime-related questions along with standard socio-economic, demographic characteristics of respondents and precise interview dates (Afrobarometer Data, 2023). The confidential version of the dataset used in this study additionally contains precise longitude and latitude information, facilitating the merging of individual responses with data on disasters from GDIS.

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[20] We are not able to test the parallel trends assumption of the difference-in-differences approach in the current cross-sectional setting which is a limitation of this study and one that has been encountered by others employing a similar approach e.g. Knutsen et al. 2017 and Isaksson and Kotsadam, 2018.

[21] The raw Kenyan sample is comprised of 2,398 observations from round 2, 1,278 observations from round 3, 1,104 observations from round 4, 2,399 observations from round 5, and 2,397 observations from round 6.

We exploit the longitude and latitude data available in both GDIS and Afrobarometer to measure the distance of disasters from the individual's sampling unit and capture disaster exposure within the specified 50km radius. Additionally, we use the dates of the interview and the disaster to determine whether the earliest record of disaster exposure occurred before or after their interview. Individuals are assigned an exposure category based on their earliest record of disaster exposure within a 15-year temporal cut-off. Following this approach, we match data on 9,576 individuals of who, 7,241 were exposed to a disaster before interview and 1,215 were exposed after interview.[22] The remaining 1,120 individuals had no exposure to disaster within 50km of their location. Figure 3 provides a map showing the distribution of individuals exposed to disaster across Kenya. Green circles indicate the individual was exposed to disaster before their interview and red circles indicate the individual was exposed to disaster after their interview. The size of the circles measures the number of exposed people in that sampling unit.

4.3.3. Variables

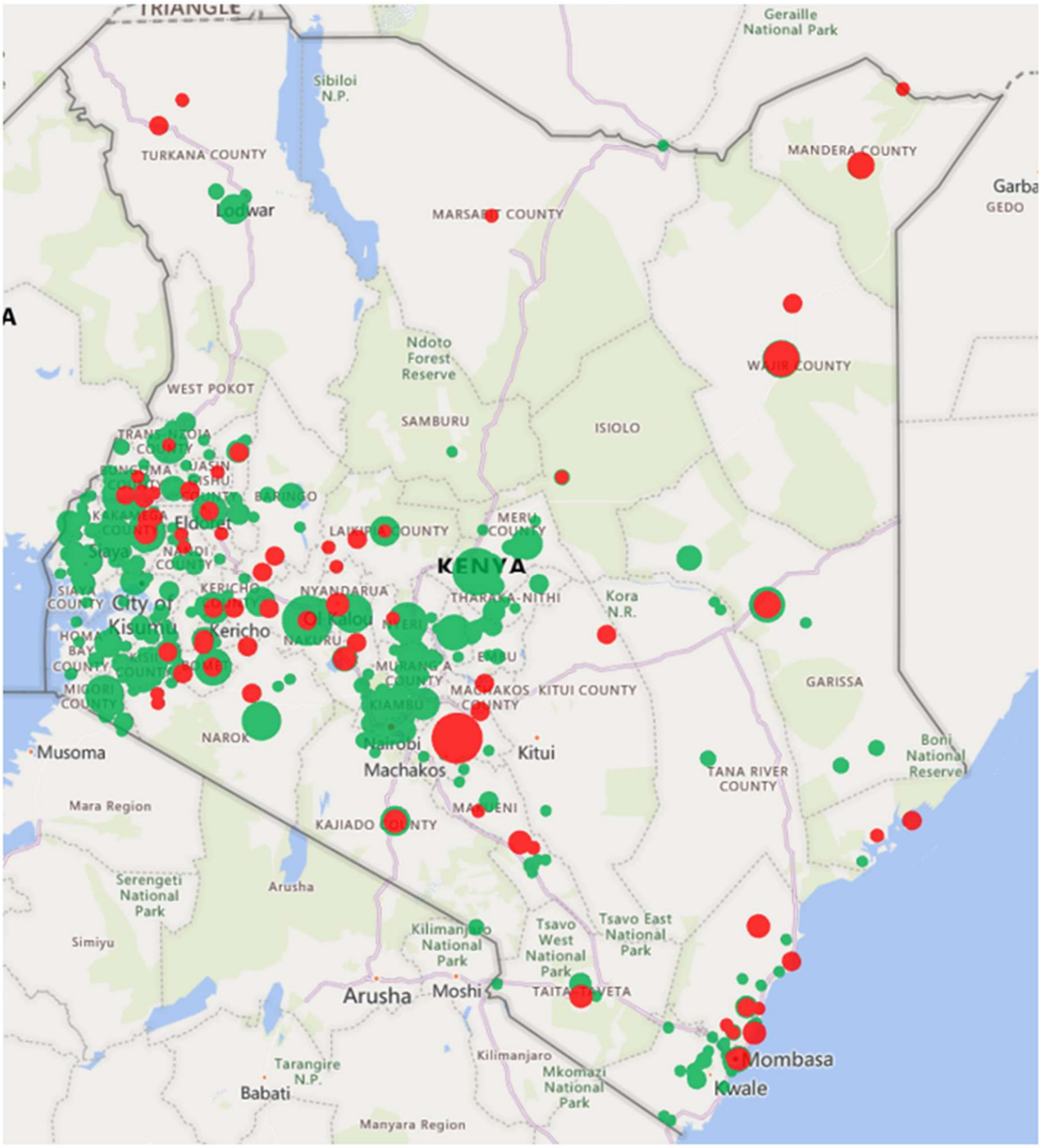
Definitions of our main dependent variables are provided in Table 8. To explore crime incidence, we utilise information on the respondents' self-reported household experiences with theft, assault and fear of crime, following existing studies based on the Afrobarometer (Fernandez and Kuenzi, 2009; Smithey and Malone, 2014; Sulemana, 2015; Söderström, 2019; Morrison and Rockmore, 2021; Gillanders et al. 2023). These variables are available across all Afrobarometer rounds used in our research.

To study *Experienced theft,* we use the responses to the question that asks individuals "During the past year, have you or anyone in your family: Had something stolen from your house?" to which, individuals may select no, once, twice, or three or more times. To look at *Physical attack*, we use the

[22] The actual sample sizes employed in the analysis are smaller due to missing observations on variables.

responses to the question that asks individuals "During the past year, have you or anyone in your family: been physically attacked?" to which, individuals may select no, once, twice, or three or more times[23].

Figure 3: Distribution of Kenyan Afrobarometer respondents by disaster exposure



Note: The circles indicate disaster exposure before or after interview. Green circles indicate exposure to disaster before the Afrobarometer survey and red circles indicate exposure after the Afrobarometer survey. The size of the circle measures the number of people exposed from each sampling unit.

[23] For *Experienced theft* and *Physical attack*, Rounds 2 – 4 provide respondents with an option of 'Always', however this was removed from Round 5 onwards.

In addition to studying actual experiences of crime, we look at individuals' fears in relation to crime. To define the variable *Fear crime*, we leverage the survey question that asks individuals "Over the past year, how often, if ever, have you or anyone in your family: feared crime in your own home?" to which, individuals may select never, just once or twice, several times, many times or always. We have coded all responses as binary with 1 indicating experiencing each type of crime at least once.

Table 8 Afrobarometer crime variable definitions

Estimation Topic	**Variables**	**Definition**	**Rounds**
Crime	Experienced theft	0-1 binary variable; equals 0 if the individual has never had something stolen from their house and equals 1 if they have had something stolen once, twice, or three or more times.	2 – 6
	Physical attack	0-1 binary variable; equals 0 if the individual has never been physically attacked and equals 1 if they have been physically attacked once, twice, or three or more times.	2 – 6
	Fear crime	0-1 binary variable; equals 0 if the individual has never feared crime in their home and equals 1 if they feared crime in their home just once or twice, several times, many times or always.	2 – 6

As discussed earlier, we exploit a difference-in-differences strategy measuring disaster exposure spatially (within 50km) and temporally (within 15-years). This approach is based on defining three variables: *exposed50_before, exposed50_after,* and *no_exposure*. *exposed50_before* and *exposed50_after* each take the value of 1 if there is a recorded disaster within 50kms either before or after interview, respectively. *no_exposure* takes the value of 1 if there is no recorded disaster within 50km either before or after interview.

Table A26 in the appendix provides the summary statistics for all variables used in our baseline model specifications (Table 9). 31 per cent of individuals report having something stolen from their home at least once, 12 per cent of individuals report experiencing physical assault at least once and 47 per cent of individuals report fearing crime in their home at least once. 83 per cent of individuals experienced some form of disaster before their interview, whilst 5 per cent experienced it after; 13 per cent of individuals are coded as having no exposure.

In terms of other characteristics, 50 per cent of our sample size is male and 34 per cent reside in an urban area, with the remaining 66 per cent residing in rural areas. The average age of the respondent in the sample is 36.

4.3.4. Results

The results of estimating equation (1) are reported in Table 9. We are interested in the difference in differences estimates, and the associated statistics.

Model (1) presents the results using *Experienced theft* as the dependent variable. The results suggest that individuals exposed to a disaster are 8.9 percentage points more likely to have experienced theft relative to those who have been exposed after. Similarly, disaster-exposed individuals are 5.3 percentage points more likely to have experienced *Physical assault* (model 2) when compared to those not yet exposed. Lastly, the results show that individuals exposed to disaster are 12.3 percentage points more likely to *Fear crime* (model 3) in their own home. Overall, our baseline results suggest that disaster struck environments are prone to increased incidence of crime. The negative coefficients on Exposed50_before and Exposed50_after terms suggest that individuals in disaster-prone areas are potentially different to those with no exposure – an observation that lends further validity to the identification approach used in the paper.

Table 9 Natural disasters and crime: Baseline analysis

	(1)	*(2)*	*(3)*
Dependent variables	*Experienced theft*	*Physical attack*	*Fear crime*
Exposed50_before	-0.006	-0.010	0.010
	(0.022)	(0.017)	(0.029)
Exposed50_after	-0.095**	-0.063**	-0.113**
	(0.038)	(0.029)	(0.047)
Difference in Differences	0.089	0.053	0.123
F-test: Exposed50_before – Exposed50_after = 0	7.066	4.767	11.199
P-value	0.008	0.029	0.001
Mean of dep variable	0.310	0.120	0.471
Sample size	7,138	7,127	7,122

R-squared	0.021	0.028	0.056

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

Do the experiences of males and females with crime post-disaster vary? Table 10 suggests that the relationship between disaster exposure and experiences of theft holds in the sample of females but not males. On the other hand, males relative to females, are at a higher likelihood of experiencing a physical attack. There is a positive relationship between disaster exposure and fearing crime in both sub-samples, with equal effect magnitudes.

Table 10 Natural disasters and crime: Analysis by gender

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Dependent variables	*Experienced theft*		*Physical attack*		*Fear crime*	
Gender	*Female*	*Male*	*Female*	*Male*	*Female*	*Male*
Exposed50_before	-0.019	0.006	0.004	-0.024	0.018	0.003
	(0.025)	(0.029)	(0.019)	(0.020)	(0.036)	(0.029)
Exposed50_after	-0.143***	-0.047	-0.036	-0.091***	-0.123**	-0.103**
	(0.046)	(0.046)	(0.035)	(0.034)	(0.054)	(0.048)
Difference in Differences	0.124	0.052	0.039	0.067	0.106	0.106
F-test: Exposed50_before – Exposed50_after = 0	8.758	1.774	1.582	5.504	6.813	7.050
P-value	0.003	0.184	0.209	0.019	0.001	0.008
Mean of dep variable	0.302	0.317	0.103	0.137	0.482	0.461
Sample size	3,566	3,572	3,560	3,567	3,557	3,565
R-squared	0.024	0.022	0.026	0.033	0.055	0.058

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

We additionally explore whether the relationship between natural disaster exposure and crime varies by urban vs rural residential status. The results reported in Table A27 show that the relationship between natural disaster exposure and crime holds in the urban sub-sample. In the rural sub-sample, individuals exposed to a disaster before the survey are at a higher likelihood of experiencing theft and fearing crime relative to those exposed after. However, the difference-in-differences estimates are insignificant when looking at experiencing physical attack. Given that our analysis based on primary collected data focuses on floods, we additionally establish in Table A28 that our results hold in the sub-sample of individuals whose disaster exposure is limited to floods.

The set of control variables utilised in the analysis is deliberately limited to arguably exogenous controls. Yet socio-economic background of individuals may have relevance to the relationship studied. In particular, previous studies have considered measures of wealth as potential factors affecting individuals' propensity to fear or fall victim to crime (Cisneros et al. 2024). We construct an asset-based wealth indicator by calculating a sum of individual ownership of radios, televisions, and vehicles mimicking the literature (Hodler et al. 2020; Ogenyi and Nchare, 2022), and re-estimate equation (1) with this variable included as a control alongside controls for unemployment and education as additional markers of socio-economic status. Table A29 presents these results showing our results are robust to controlling for measures of individual socio-economic status.

Our sample includes individuals never exposed to a disaster based on the definitions employed. In an effort to arguably enhance our identification setup further, we simply drop individuals with no exposure to a disaster from the sample thereby simply drawing direct comparisons between exposed before and exposed after individuals. These results are shown in Table A30 and confirm the robustness of our central findings to this change in the model specification.

We lastly consider the robustness of our results to changes in cutoffs used to define temporal and spatial exposure to disasters. First, we employ 5-year and 10-year cut-offs, instead of 15-year cut-off, to define temporal exposure to disasters. The results reported in Table A31 show that our results mostly remain robust with the difference-in-differences estimate insignificant for our 5-year cut-off-based model of physical assault. We also check the robustness of the results to employing alternative cut-offs for spatial exposure in 10-km increments in the 10km to 100km range. The results shown in Table A32 are largely robust. Especially when employing larger spatial cut-offs, we observe increased difference-in-differences estimates for our measures of experiencing theft and fearing crime. What this suggests is that crime may not necessarily be siloed to the epicentres of disasters.

Overall, our analysis suggests a robust positive link between disaster exposure and crime in a large sample of individuals. Next, we turn to taking a closer look at the relationship and the potential transmission mechanisms through analysis of primary data collected in a post-disaster context in the Baringo region of Kenya.

4.4. Natural disasters and crime: Evidence based on primary data from Baringo, Kenya

Our primary data collection in the Baringo region of Kenya aimed to achieve a closer understanding of how and why natural disaster exposure might induce crime. This section provides a description of the data collection, followed by the results based on (descriptive) quantitative and qualitative analysis of the data.

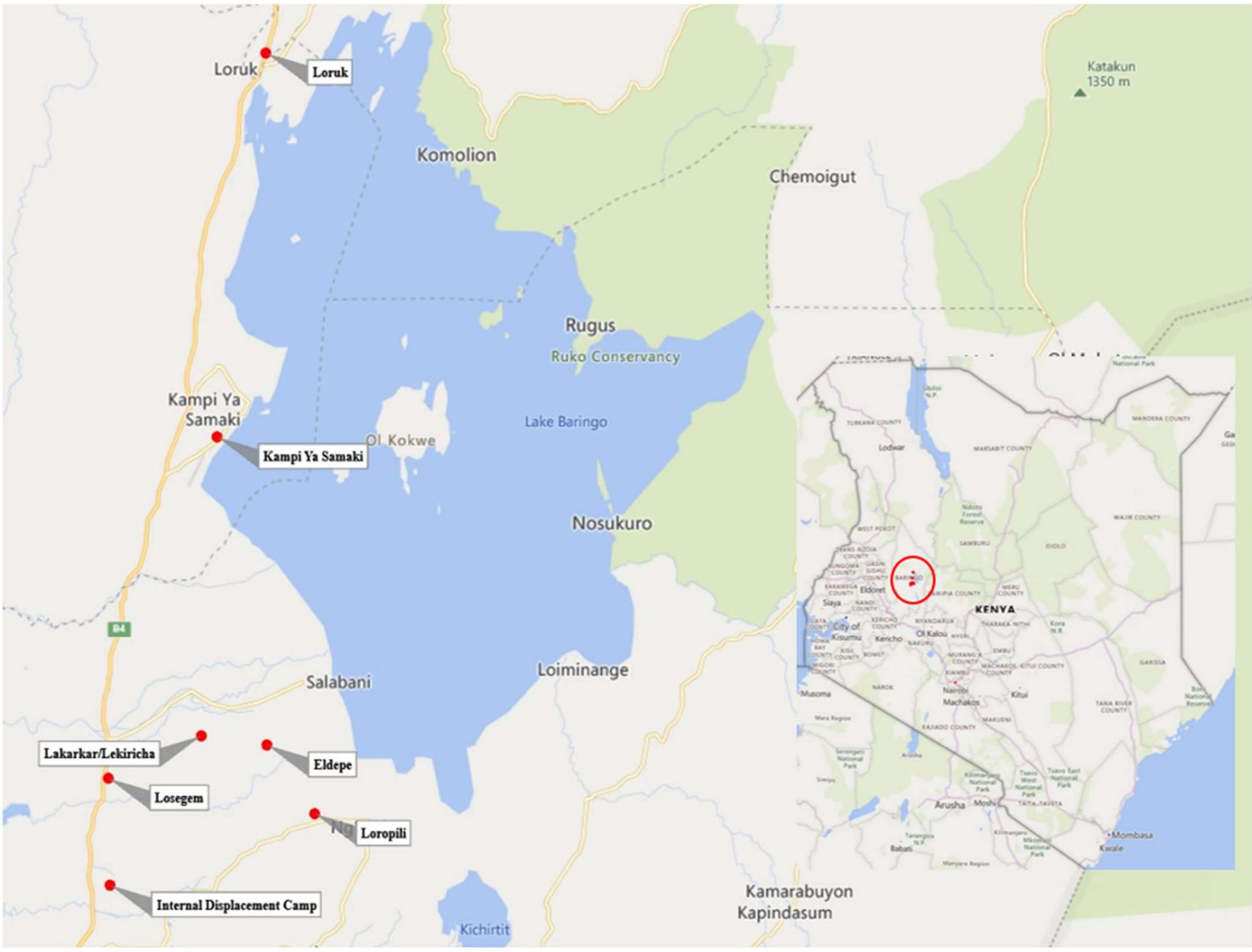
4.4.1. Primary data collection and sample

We conducted detailed semi-structured interviews (the set of interview questions used in this study can be found in Appendix B) with individuals affected by the 2020 East Valley Rift flooding in Baringo, Kenya. The Baringo region was selected as our case study, given its recent exposure to a major flood that affected a large number of inhabitants of the area.

We utilised the services of a Kenyan based NGO (Divinity Foundation) to work with the affected communities to identify participants for the interview. Ethical considerations were a key factor in the study design. Revisiting instances of disaster can be traumatic for the subjects and commenting on the government/institutional response has associated risks. We therefore designed our questionnaire in consultation with local Kenyan representatives to mitigate the risk of emotional distress throughout the interview and provided participants with the contact for a free and available local organisation supporting individuals with emotional trauma. All interviews with individuals were audio recorded with consent and the data was then translated from the local dialect (predominantly Swahili) to English by a locally engaged translator. All responses have been de-identified to preserve the anonymity of the respondents.

We were able to complete interviews with 75 individuals across 8 communities with 50 from the Njemps ethnic group, 15 from the Turgen ethnic group and 10 from the Pokot ethnic group. Within each of the three affected communities (Njemps, Pokot, Turgen), we sought to recruit participants based on their proximity to the lake with the Njemps ethnic group representing the majority of those living closest to the lake and therefore making up a majority of our sample, whilst the Pokot ethnic group lived the furthest from the lake and represents the smallest sample share. All respondents lived within 15 kilometres of the lake at the time of the disaster. Figure 4 provides a map of the Lake Baringo and interview locations.

Figure 4: Lake Baringo: interview sampling locations



Note: The map captures our sampling locations within the Baringo region. Sampling locations captured by the red dots include Eldepe, Kampi Ya Samaki, Lakarkar, Lekiricha, Loropili, Loruk, Losegem and the Internal Displacement Camp. Lakarkar and Lekiricha sampling villages share the same geolocation. The smaller rectangle map highlights the location of our case study on the map of Kenya.

Interview participants were selected to represent a spread of ages and genders. As Table 11 shows, individuals in the sample are aged from 18 to 83 years old with an average age of 41. 55 per cent are male, 84 per cent are married and 88 per cent are Christian (the remaining respondents are Traditional African Spiritualist). 55 per cent report gaining their main source of livelihood from agriculture. Lastly, 47 per cent have a secondary or above education (with only 16 per cent of respondents having received a tertiary education).

Our analysis proceeds at two levels, at an individual level across the 75 respondents and at a crime level. Guided by the approach of Baron et al. (2023), we provided individuals with multiple crime scenarios to understand how the individuals view crime and the possible reasoning driving criminal acts, in addition to eliciting information on their own crime experiences. We provided four hypothetical scenarios concerning different crimes (theft, assault, property crime, ethnic conflict) and additionally recorded information on up to two real examples of crime provided by the respondent. Our crime-level dataset based on combining observations from both the hypothetical and real crime scenarios, consists of 429 observations (300 hypothetical scenarios and 129 real examples).

4.4.2. Variable definition

Interview transcripts were coded by the research team. Where individuals were asked closed-ended questions, their answers were recorded and coded during the interview. No answer for any question was coded as -1 or missing. Respondents were first asked a series of demographic questions concerning their age, gender, religion, marital status, number of children, employment, main source of income, education level, and ethnic group. They were also asked to self-report their levels of flood exposure across a range of severity measures, as well as their perception of whether certain types of crimes have increased. Respondents rated the severity of the impact on their property, income, job, psychological distress, livestock, land, and assets on a scale of severe or not. Similarly, respondents rated the frequency of crimes including theft, assault, property crime (vandalism) and ethnic crime on a scale of increased or not.

Where individuals were asked open-ended questions, we coded these based on the translated transcript and took note of all possible responses prior to categorising them. To explore the perceived benefits of committing a crime, we leverage the open-ended question 'What, if any, are the benefits to committing a crime like this?' with individuals responding that there was no benefit, the benefit was reward, the benefit was survival, or the benefit was outweighed by the punishment. To explore the perceived costs of crime, we use the open-ended questions 'What is the probability of being caught doing this in your community?' and 'Do you think the punishment for this crime prevents people from doing it?'

To complement our cost-benefit analysis of crime, we use a series of yes/no crime heuristics questions including: 'Do you think individuals would commit more crimes if there was less authority?', 'Do you think natural disasters create an opportunity for more crime?', 'Do you think a corrupt government encourages more crime?', 'Do you think your local government is currently corrupt?', 'Do you think men have more to gain by committing a crime?', 'Do you think the benefits of committing a crime are increased after a disaster?', 'Do you think individuals would commit more serious crimes if the reward were larger?', and lastly 'Do you think individuals see crime as a way of regaining what they lost during a disaster?'.

For further discussion on crime-related reasoning, we pool responses from the hypothetical open-ended question 'Why do you think a natural disaster would make it easier for crime X to occur?' and from the real crime open-ended question 'Why do you think the individual did it?' Responses to both questions included opportunity [1], vulnerability [2], emotion [3], competition [4], other [5]. Lastly, to explore the triggers of crime, we use the open-ended question 'Do you think rational thought or emotion triggers an individual's choice to commit crime X?'. The coding options for these open-ended questions are included in Appendix B.

4.4.3. Results

Our analysis of the primary data proceeds in three steps. First, we confirm the relationship between disaster exposure and crime, drawing on the individual-level dataset generated from the primary data.

Given the disaggregated data collected by severity of disaster impact and crime type, this exercise offers the opportunity to study heterogeneities in the link. Second, we utilise the crime-level dataset generated through individual responses to crime-related questions based on real-life and hypothetical scenarios, to provide a quantitative descriptive analysis of possible mechanisms underlying the link between natural disaster exposure and crime. Third, we utilise the responses to open-ended questions to conduct a qualitative content analysis to provide further insights on the mechanisms.

4.4.3.1. Flood and crime

Table 12 provides a descriptive analysis of the relationship between being severely affected by a disaster and reporting an increase in crime incidence. The patterns in Baringo data largely mirror those found in the Afrobarometer data suggesting that severe disaster exposure is associated with an increase in crime.

Regardless of the type of the impact a disaster has had on an individual, a severe impact appears to be associated with an increased reporting of crime. However, there are some heterogeneities. 98 per cent of individuals who report that their income has been severely affected by the disaster report an increase in at least 1 crime while only 88 per cent report an increase in at least 1 crime of those who do not report a severe income effect due to the disaster.

100 per cent of individuals who report that their assets have been severely affected by a disaster report an increase in at least 1 crime compared to 88 per cent reporting that at least 1 crime increased among those who do not report a severe asset effect associated with the disaster. Similarly, 97 per cent of individuals who report severe disaster impacts on their property, job, psychology or livestock report an increase in at least 1 crime type while 84 per cent (property), 90 per cent (job), 89 per cent (psychology), and 91 per cent (livestock) report an increase in at least 1 crime type among those who do not report severe effects in these categories.

Table 13 presents the increase in reported crime by gender. 93 per cent of individuals in the sample report an increase in at least 1 crime in the post-flood period. The share of individuals who report an increase in at least 1 crime is higher among males (98 per cent) compared to females (88 per

Table 11 Natural disasters and crime: Baringo individual-level summary statistics

	Villages								
	All	*Eldepe*	*Kampi Ya Samaki*	*Larkarkar*	*Lekiricha*	*Loropili*	*Loruk*	*Losegem*	*IDP Camp*
% Male	0.55	0.70	0.11	0.50	0.50	0.60	0.60	0.80	0.45
Mean age	40.91	40.30	47.44	28.33	34.75	46.60	39.50	49.90	30.55
% Married	0.84	1.00	0.89	1.00	1.00	0.73	0.70	0.90	0.73
Mean no. of children	4.99	7.20	3.44	2.00	2.75	5.53	5.50	6.40	4.18
% Christian	0.88	0.90	1.00	1.00	0.75	0.80	1.00	0.80	0.82
% Secondary or higher education	0.47	0.30	0.33	1.00	1.00	0.27	0.70	0.40	0.45
% Agriculture income	0.55	0.70	0.11	0.50	0.50	0.60	0.33	0.70	0.82
Sample size	75	10	9	6	4	15	10	10	11

Note: The IDP Camp refers to the Internal Displacement Camp and is a location where persons were relocated from multiple areas yet is no more than 15 kilometres from the individuals original home. All villages are fully ethnically homogenous; in the full sample, 67 per cent is from the Njemps ethnic community. Secondary or higher education refers to the percentage of individuals who have secondary or higher education. Agriculture income refers to the percentage of individuals who receive their primary income from agriculture.

Table 12 Natural disasters and crime: means of increase in crime types by flood exposure

	Impacted by the flood:													
	Property impacted severely		*Income impacted severely*		*Job impacted severely*		*Psychology impacted severely*		*Livestock impacted severely*		*Land impacted severely*		*Assets impacted severely*	
	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
% Theft increased	0.84	0.84	0.76	0.90	0.78	0.91	0.75	0.92	0.84	0.84	0.83	0.86	0.79	0.90
% Assault increased	0.49	0.66	0.44	0.62	0.53	0.61	0.61	0.53	0.50	0.68	0.49	0.67	0.56	0.59
% Property crime increased	0.64	0.65	0.61	0.68	0.63	0.65	0.59	0.71	0.58	0.73	0.66	0.63	0.62	0.69
% Ethnic crime increased	0.75	0.73	0.71	0.76	0.69	0.79	0.68	0.79	0.77	0.70	0.77	0.71	0.76	0.72
% At least one crime increased	0.84	0.97	0.88	0.98	0.90	0.97	0.89	0.97	0.91	0.97	0.93	0.94	0.88	1.00
Sample size	37	38	34	41	40	34	36	38	44	31	40	35	43	30

Note: Impact columns refer to severely (Yes) vs moderately or not at all (No). At least one crime increased is calculated by coding as 1 if at least one of the crime types recorded a 2 (increased).

cent). There are differences in crime type, however. We find that for both genders, theft saw the highest increase (85 per cent for males and 82 per cent for females). Notably, reports of increased assaults were 24 percentage points higher among males while reports of increased ethnic crime are higher among females.

Table 13 Natural disasters and crime: means of increase in crime by gender

	Sub-samples		
	Males	*Females*	*Full sample*
% Theft increased	0.85	0.82	0.84
% Assault increased	0.68	0.44	0.57
% Property crime increased	0.68	0.61	0.64
% Ethnic crime increased	0.70	0.79	0.74
% At least one crime increased	0.98	0.88	0.93
Sample size	41	34	75

Note: At least one crime increased is calculated by coding as 1 if at least one of the crime types recorded a 2 (increased).

Now that we have established a pattern highlighting an increase in crime in response to disaster exposure, we turn to the analysis of underlying mechanisms, based on individuals' perceptions.

4.4.4. Mechanisms: quantitative insights

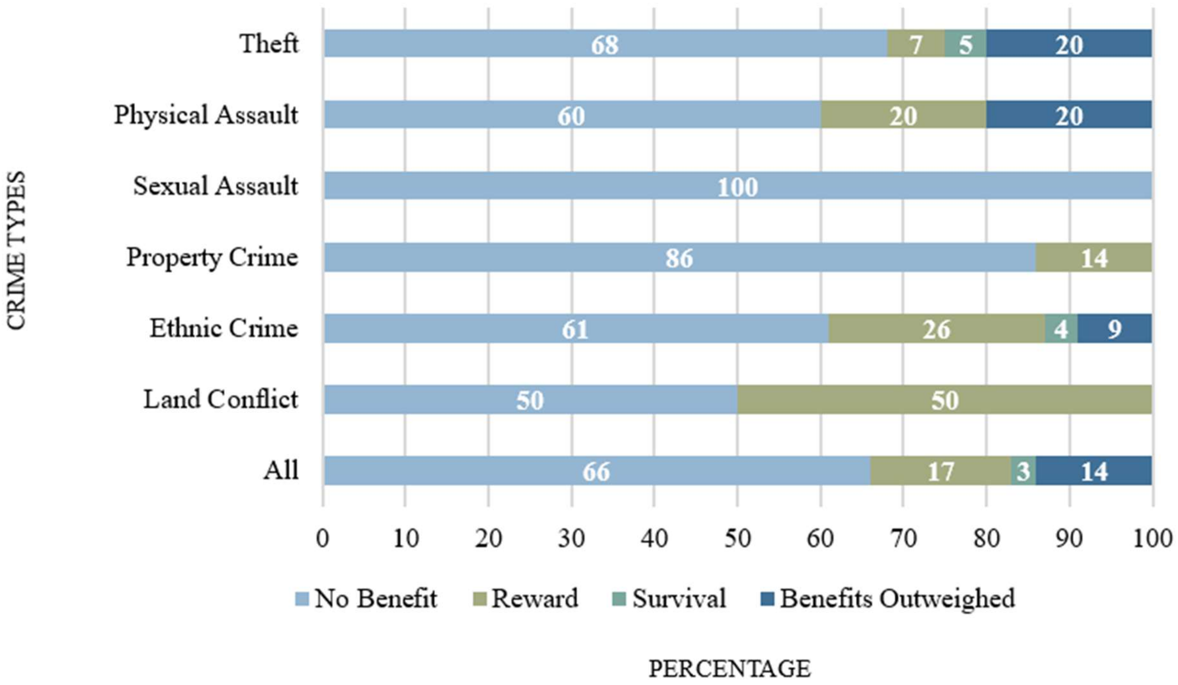
We start with exploring whether cost-benefit considerations are at play in explaining the relationship between natural disasters and crime. Our analysis follows the frameworks by Becker (1968), Sah (1991) and Freeman (1999) to explore whether disaster exposure is associated with changes in the benefits and/or costs of engaging in crime.

Figure 5 presents the distribution of responses to the question on perceived benefits of crime, by crime type, using a crime level dataset based on real-life crime scenarios.[24] Across all crime types,

[24] Hypothetical crime scenarios are not included in this figure as the question concerning benefits was only asked during the real-life crime scenarios.

at least 50 per cent of individuals say there was no benefit for committing a crime. In the case of some crimes, however, there is a perception of rewards, and in some cases, individuals perceive that the benefits outweighed the costs. For example, in the case of land conflict, half of the individuals perceive that there is a reward associated with committing a crime. In the case of ethnic crime, 26 per cent of individuals share that belief. In the case of a theft and physical assault, a fifth of individuals believe that the costs outweigh the benefits.

Figure 5: Perceived benefits of committing a crime, by crime type

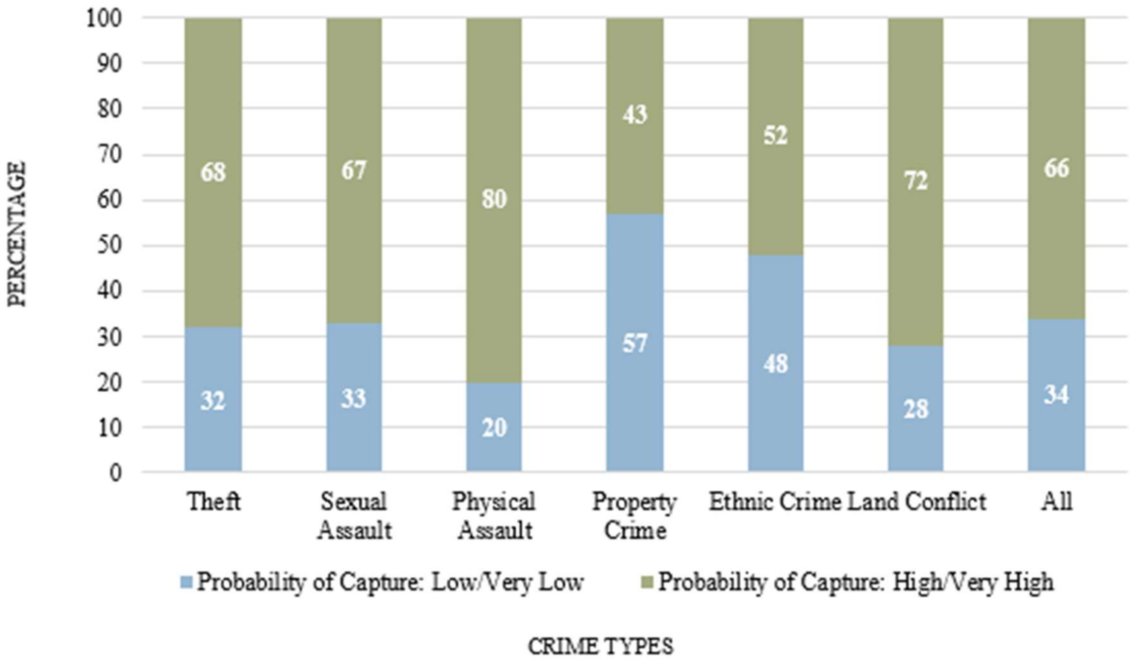


Note: The figure is based on the dataset of real-life crime scenarios with a sample size of 132. For all real-life crime examples, respondents were asked "What, if any, are the benefits to committing a crime like this?" and respondents provided open-ended qualitative answers, which were coded by the research team afterwards. Categories were developed during coding to encompass all provided options by respondents. All answers provided by respondents fell under one of the four categories.

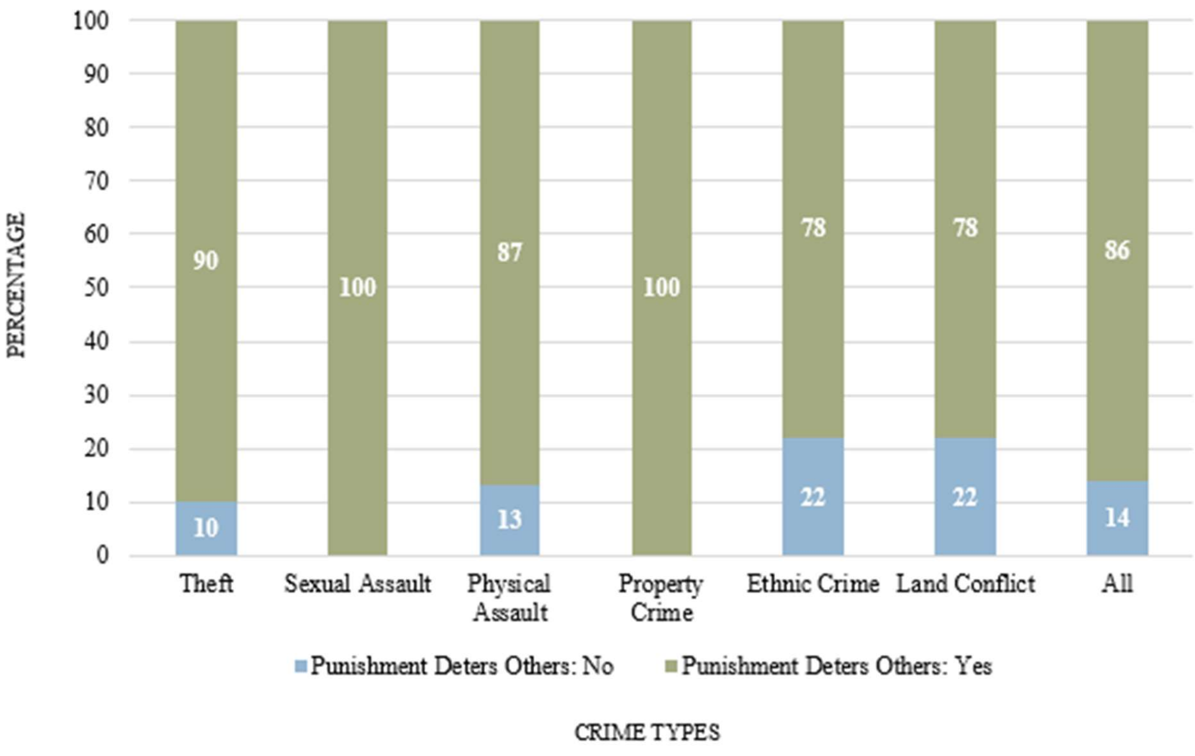
We next explore the perceptions of costs of committing a crime (capture and/or punishment) in Figure 6, panels A and B, by looking at the perceived probabilities of capture and whether punishment deters people from doing it by crime type.

Figure 6: Perceived costs of crime by, crime type

Panel A: Probability of capture



Panel B: Punishment deters others

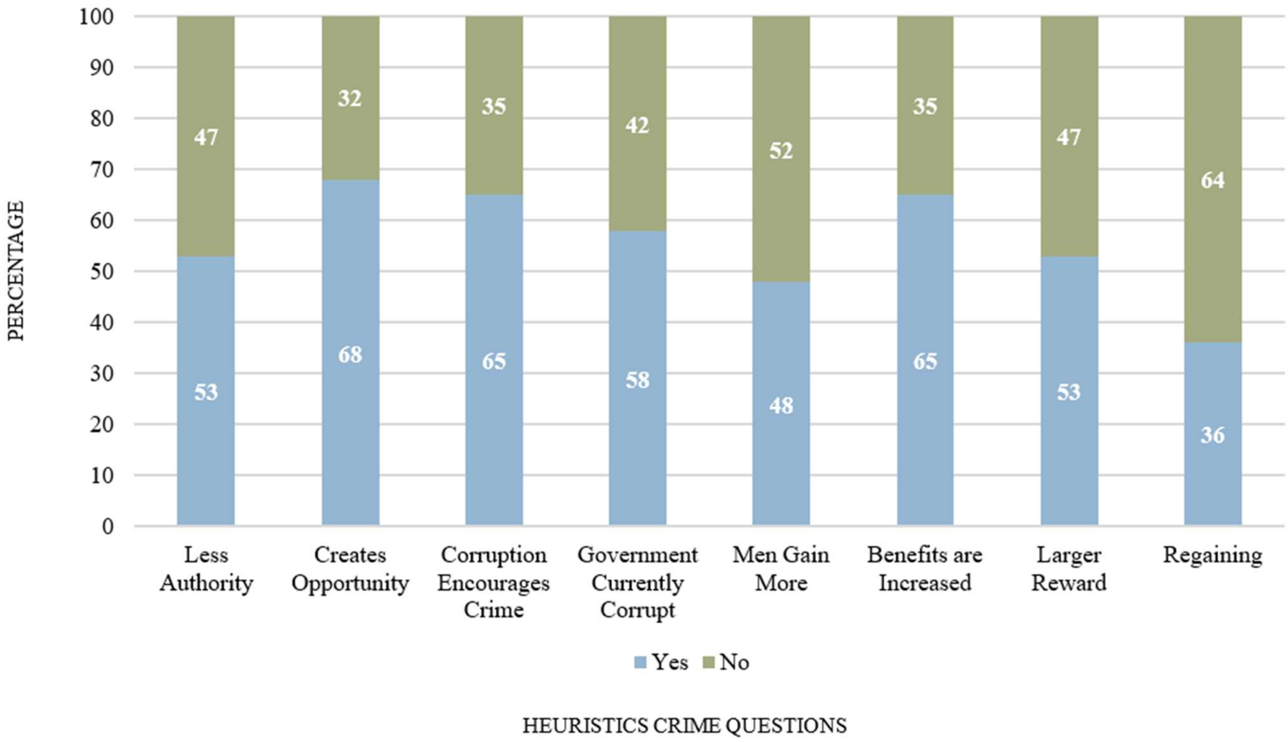


Note: The figure is based on the dataset of real-life crime scenarios with a sample size of 132. For all real-life crime examples, respondents were asked "What is the probability of being caught doing this in your community?" and respondents provided open-ended qualitative answers, which were coded by the research team afterwards. Respondents were also asked “Do you think the punishment for this crime prevents people from doing it? Why?” and respondents provided open-ended qualitative answers, which were coded by the research team afterwards. Categories were developed during coding to encompass all provided options by respondents. Respondents were reluctant to expand upon their answers beyond a yes/no response and responses were therefore coded as such. All answers provided by respondents fell under one of the two categories.

These questions were once again only asked following the description of real-life crime scenarios. We find that for most crimes, the probability of capture is deemed to be high on average. However, in the case of property crime, over half of the individuals perceive that the probability of being caught is low. Close to half of the individuals think the probability of capture is low in the case of committing an ethnic crime. We also find that for all crimes, punishment is seen as an effective deterrent.

To complement the analysis of perceived benefits and costs of committing a crime, we asked the survey respondents a series of heuristic questions designed to measure the participants’ attitudes towards crime. As we see in Figure 7, a majority (53 per cent) of participants believe more crimes would be committed with less authority. A majority (68 per cent) also believe that disasters create an opportunity for more crime. We observe that 58 per cent believe their local government is currently corrupt and 65 per cent believe that government corruption encourages more crime. Lastly, a majority (65 per cent) indicate that the benefits to crime are increased after a disaster and 53 per cent agree individuals would commit more serious crimes for a larger reward.

Figure 7: Attitudes to crime: responses to heuristic questions

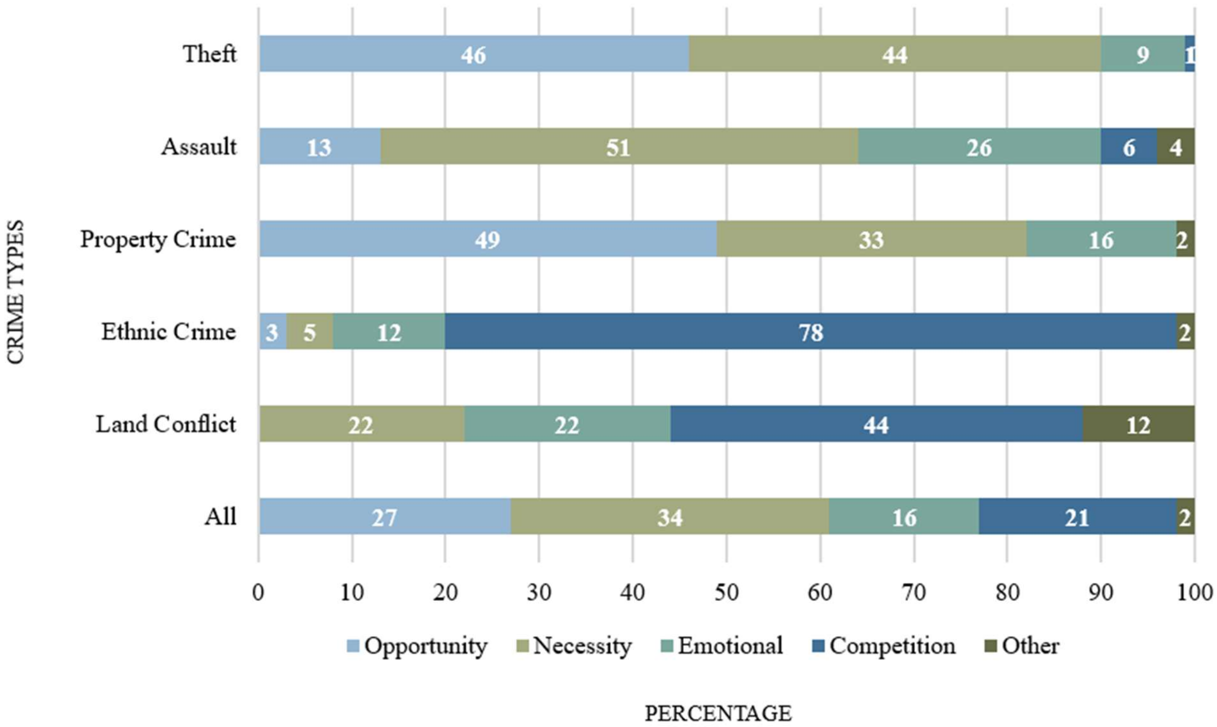


Note: The figure is based on individual-level dataset with sample size of 75 except for the item *Corruption encourages crime*, which has a sample size of 74. Respondents were asked 8 questions and were asked to give a yes/no answer within 10 seconds. For *Less authority*, respondents were asked "Do you think individuals would commit more crimes if there was less authority?". For *Creates opportunity*, respondents were asked "Do you think natural disasters create an opportunity for more crime?". For *Corruption encourages crime*, respondents were asked "Do you think a corrupt government encourages more crime?". For *Government currently corrupt*, respondents were asked "Do you think your local government is currently corrupt?". For *Men gain more*, respondents were asked "Do you think men have more to gain by committing a crime?". For *Benefits are increased*, respondents were asked "Do you think the benefits of committing a crime are increased after a disaster?". For *Larger reward*, respondents were asked "Do you think individuals would commit more serious crimes if the reward were larger?". For *Regaining*, respondents were asked "Do you think individuals see crime as a way of regaining what they lost during a disaster?".

To gain further insights into the perceptions of criminal behaviour in a post-disaster context, we draw on questions that explicitly elicit information on the motivation underlying a criminal behaviour in a pooled sample of hypothetical and real-life crime scenarios. Figure 8 explores this by crime type and suggests that theft and property crime are perceived to be mostly motivated by opportunity (46 per cent and 49 per cent respectively), assault by necessity (51 per cent), and ethnic and land conflict by competition for resources (78 per cent and 44 per cent respectively). Yet, a non-negligible share of individuals see a role for emotionally induced crime in a post-disaster setting. The latter is in line with expressive theories of violence (Feshbach, 1964; Salfati and Canter, 1999; Salfati, 2000; Thijssen and de Ruiter, 2011), whereby crime serves as a vehicle to relieve stress, in this case, stress caused by exposure to a natural disaster.

Appendix Figure B1 explores whether crime reasoning provided by individuals varies when applied to real-life versus hypothetical crime scenarios. For hypothetical crimes, individuals overwhelmingly indicate that necessity (46 per cent) drives criminal acts the most, and yet in comparison when looking at real crime scenarios, only 19 per cent indicate necessity as the key driver, rather individuals responded that opportunity (29 per cent) and emotion (30 per cent) drive criminal behaviours. One possible reason for this may be that when considering hypothetical crime, individuals are more empathetic to broader social factors, yet when crime directly affects the individual, self-preservation takes over.

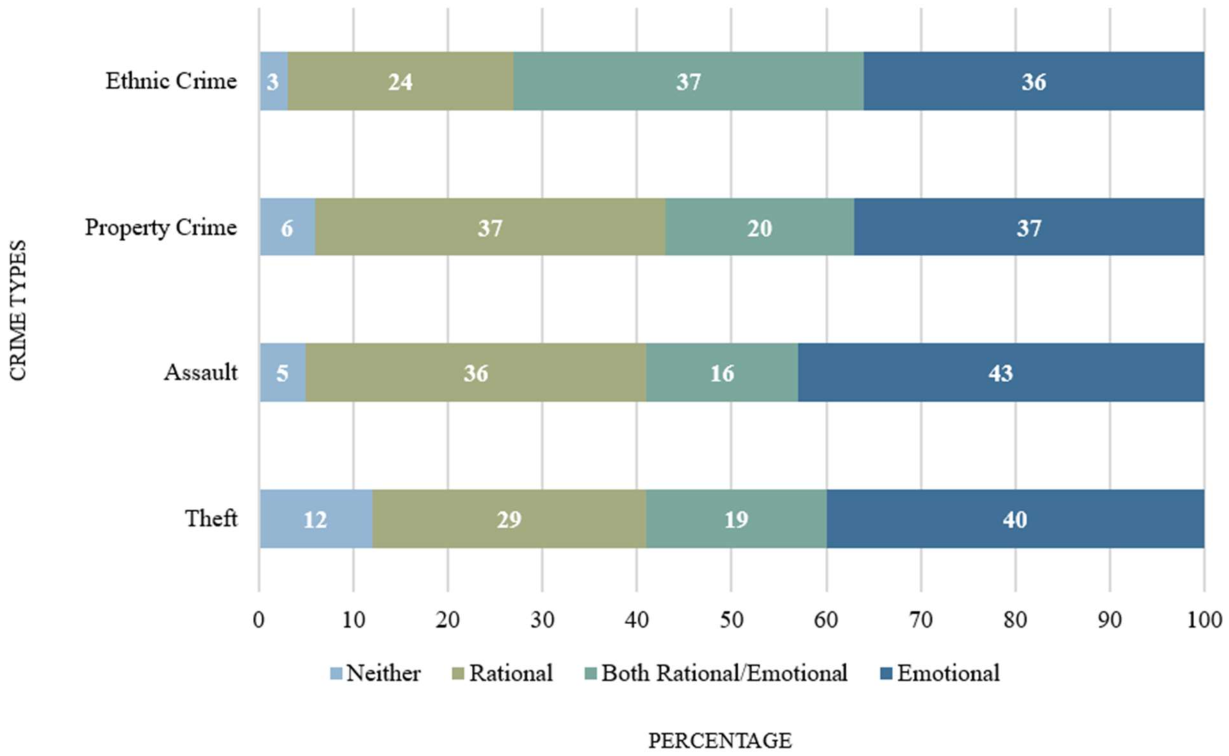
Figure 8: Crime reasoning, by crime type



Note: The figure is based on the pool dataset of real-life and hypothetical crime scenarios with a combined sample size of 429. For all crime types, respondents provided open-ended qualitative answers and responses were coded by the research team afterwards. Categories were developed during coding to encompass all provided options by respondents. For real crime examples, respondents were asked “Why do you think the individual did it?”. For hypothetical crime examples, respondents were asked one of the following depending on the crime type: “Why do you think a natural disaster would make it easier for individuals to steal?”, “Why do you think a natural disaster would make assaults more frequent?”. “Why do you think a natural disaster would increase property crime?”, “Why do you think a natural disaster would make it easier for ethnically motivated crime to occur?”. All answers provided by respondents fell under one of the five categories.

Based on this analysis, criminal behaviour may not always be motivated by cost-benefit considerations; in some cases crime may be a route of relieving compounded stress or emotional build-up caused by disaster. This emotional resolve likely provides the individuals with the utility required to offset the cost of committing a crime. Figure 9 explores the role of emotional and rational triggers in crime, by crime type. The question regarding crime triggers was asked exclusively for hypothetical crime scenarios. We find that both triggers are seen to play a role in criminal behaviour. In the case of theft and assault, at least 40 per cent of individuals believe that emotion is at play in triggering crime. In the case of property crime, equal shares of individuals (37 per cent) perceive crime to be driven by emotional vs rational triggers while 20 per cent think both are at play. Finally, in the case of ethnic crime over half of the individuals see a role played by rational consideration, and in the case of 37 percent, in combination with emotional triggers.

Figure 9: Emotional and rational triggers of crime, by crime type



Note: The figure is based on the hypothetical crime scenarios with a sample size of 300. For all hypothetical crime examples, respondents were asked "Do you think rational thought or emotion triggers an individual's choice to steal/commit assault/perform property crime/commit ethnically charged crime? Why?" and respondents provided open-ended qualitative answers, which were coded by the research team afterwards. Categories were developed during coding to encompass all provided options by respondents. Respondents were reluctant to expand upon their answers beyond a neither/both/rational/emotional response and responses were therefore coded as such. All answers provided by respondents fell under one of the four categories.

Overall, the descriptive analysis of the interview data suggests that both cost-benefit considerations and stress induced by a disaster are likely at play in motivating criminal behaviour. Next, we turn to the analysis of qualitative open-ended responses provided by respondents.

4.4.5. *Mechanisms: qualitative insights*

The analysis of emerging and recurrent themes in individuals' responses to questions on why natural disasters lead to increase in crime, and what the perpetrators motives are, are in line with the findings of the descriptive analysis of interview data.[25]

Respondents provided a series of contextual and specific reasons as to why they believed crime was more frequent post-disaster. Economic circumstances of an individual hit by a disaster were a prominent theme in responses. We see respondents indicating that "since flooding has destroyed the households source of livelihood this makes people desperate" (BNG001) and that crime may emerge as a result of "economic hardships brought about by floods" (BNG022). Another respondent highlighted that crime emerged "because the victims don't have alternatives" (BNG045).

Respondents also shared their views on perpetrators' motives for committing crime. Some respondents indicated that individuals may see crime "as an opportunity to address economic challenges" (BNG012). Others thought crime in a post-disaster setting was a means to improve one's economic position. Respondents highlighted crime as an opportunity of "enriching themselves" (BNG005) and that "people saw an opportunity of getting things they did not possess easily" (BNG048).

In addition to economic hardships, considerations of inequality and competition over scarce resources featured in the responses provided by participants. One respondent specified that "communities are desperately struggling for scarce resources and there is no mechanism on how it will be shared equally" (BNG048). This resource competition "can easily motivate ethnic clashes due to competition" (BNG004). The movement of individuals can also trigger crime as one respondent says that "by migrating to a new location, the victims of floods are considered to be less privileged individuals who have no rights" (BNG021), whilst other respondents shared similar sentiments that "when people densely settle in the same piece of land, there will be social problems" (BNG061) and issues arise from a "congestion of people from different places with different behaviours" (BNG068).

[25] As responses were provided in the individuals native tongue and then translated, grammar and sentence structure has been altered slightly for the paper.

Respondents also made references to the changes in circumstances that reduced the costs of committing a crime, including “thieves take advantage of overcrowding” (BNG069), “victims left their belongings unguarded” (BNG010) and as “the victims do not have the ability to report them (the criminal)” (BNG040) the “chances of being caught has been very minimal” (BNG037). It was also noted that “criminals will take advantage of the situation” (BNG049) and utilise the victims confusion as an opportunity to commit crime.

Some of the reasoning offered by the participants is in line with emotionally fuelled violence. Respondents say that some individuals may “resort to such crimes as a way of displaying their frustrations” (BNG006) brought about by the floods. Alternatively, responses also capture residual emotional tension specifying that “some individuals may view it as an opportunity of settling grudges they had previously before flooding” (BNG023). Furthermore, it was noted that individuals saw crime “as an opportunity for vengeance” (BNG006) and that it was perceived to be further motivated “due to ethnic hatred amongst those communities” (BNG023). We also observe actions fuelled by the history of pastoral conflict as one respondent says, “dishonest individuals will take advantage of the invisible boundaries to claim a piece of land that doesn’t belong to them” (BNG024) or that the individual “claims ancestral land and they have a right to reclaim” (BNG067).

Overall, these qualitative insights add further support to the quantitative patterns pointing towards the role of cost and benefit considerations as well as stress induced by exposure to a natural disaster in leading to increased occurrences of crime post-disaster. Respondents tend to see criminal behaviour as a strategy to mitigate or improve one’s economic circumstances post-disaster. Some of the responses also suggest a decrease in costs of committing a crime post-disaster, including a lower chance of being caught. Yet, some responses reflect the context of historical pastoral and ethnic conflict in Kenya whereby the stress of the disaster may allow old grudges to re-emerge.

4.5. Conclusion

Natural disasters alter the prevalence of crime. Whether the observed effect is positive due to prosocial behaviours induced by a disaster, or negative due to social tensions and inequalities resulting from it, remains an open question. We revisit this question drawing on a case study of Kenya where natural disasters and crime are highly prevalent.

Using both geocoded quantitative data from Afrobarometer and GDIS, and primary qualitative data, we find that the association between natural disaster exposure and crime in the context of Kenya is positive. Our quantitative estimates based on difference-in-difference models suggest that individuals exposed to a disaster experience greater crime incidence and fear of crime compared to individuals yet to be exposed to a disaster (those whose interview preceded a disaster exposure). These findings are robust to a series of tests.

We complement this finding with primary collected data from Baringo, Kenya with over 90 per cent of the 75 individuals interviewed perceiving an increase in at least one type of crime post-disaster. The analysis of primary data also explores the potential mechanisms driving crime incidence and we find results that suggest the role of cost benefit considerations as well as stress in increased criminal behaviour following a disaster. The disaster context creates an environment with greater crime opportunity and less risk which is likely to translate into more frequent incidence of crime. We also observe that emotional frustrations and residual ethnic conflict are seen to motivate crime, heightened by the resource tensions created by disaster.

While this study provides important contextual insights into individuals' perceptions of crime in the context of a region exposed to the impacts of a natural disaster, it is essential to acknowledge the potential limitations in relying solely on these perceptions to explain criminal motivations. Surveyed individuals in Kenya may be aware of pre-existing cultural narratives such as the relationship between poverty and crime, and their responses may be motivated by this and their ongoing experiences with ethnic conflict. Surveyed individuals may have also been tempted to exaggerate the severity of their experience in the interest of directing more aid to their communities. Lastly, given the complex nature of criminal behaviour, further research incorporating the perspectives of perpetrators would be beneficial in developing a comprehensive understanding of crime patterns during natural disasters. While these limitations do not negate the findings of our research, they do present potential avenues for future research.

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4.7. Appendix A: Natural disasters and crime: Evidence based on Kenyan Afrobarometer survey

Table A26: Baseline Afrobarometer summary statistics

	Experienced theft	*Physical attack*	*Fear crime*
		Mean	
Experienced theft	0.310		
	(0.462)		
Physical attack		0.120	
		(0.325)	
Fear crime			0.471
			(0.499)
Disaster exposure (50km – before)	0.826	0.826	0.827
	(0.379)	(0.379)	(0.379)
Disaster exposure (50km – after)	0.046	0.046	0.046
	(0.209)	(0.209)	(0.209)
Disaster exposure (50km – no exposure)	0.128	0.128	0.127
	(0.334)	(0.334)	(0.334)
Male	0.500	0.500	0.501
	(0.500)	(0.500)	(0.500)
Urban	0.337	0.336	0.337
	(0.473)	(0.473)	(0.473)
Age	35.800	35.802	35.799
	(13.479)	(13.484)	(13.481)
Region (Nairobi)	0.102	0.101	0.101
	(0.302)	(0.302)	(0.302)
Region (Central)	0.126	0.126	0.126
	(0.332)	(0.331)	(0.332)
Region (Eastern)	0.149	0.149	0.149
	(0.356)	(0.356)	(0.356)
Region (Rift Valley)	0.240	0.240	0.239
	(0.427)	(0.427)	(0.427)
Region (Nyanza)	0.135	0.135	0.135
	(0.342)	(0.342)	(0.342)
Region (Western)	0.107	0.107	0.107
	(0.309)	(0.309)	(0.309)

Region (Northeastern)	0.054	0.054	0.054
	(0.225)	(0.226)	(0.225)
Region (Coast)	0.088	0.088	0.089
	(0.284)	(0.284)	(0.284)
Sample size	7,138	7,127	7,122

Note: Summary corresponding to models 1 (*Experienced theft*), 2 (*Physical attack*) and 3 (*Fear crime*) of our baseline results, Table 2. Standard deviations are in parentheses.

Table A27 Natural disasters and crime: Analysis by urban/rural residence

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Dependent variables	*Experienced theft*		*Physical attack*		*Fear crime*	
Residential status	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*
Exposed50_before	0.002	-0.064*	-0.013	0.018	0.005	0.006
	(0.027)	(0.036)	(0.020)	(0.026)	(0.032)	(0.055)
Exposed50_after	-0.088*	-0.148***	-0.048	-0.0877**	-0.118**	-0.099
	(0.049)	(0.044)	(0.037)	(0.036)	(0.059)	(0.074)
Difference in Differences	0.090	0.083	0.035	0.094	0.123	0.105
F-test: Exposed50_before – Exposed50_after = 0	4.105	5.951	1.284	12.253	5.507	3.946
P-value	0.044	0.016	0.258	0.001	0.020	0.048
Mean of dep variable	0.306	0.316	0.108	0.145	0.452	0.511
Sample size	4,732	2,406	4,729	2,398	4,723	2,399
R-squared	0.024	0.018	0.020	0.040	0.062	0.041

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender; urban dummy is omitted given the sub-sample analysis by urban/rural status), sub-national region and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

Table A28 Natural disasters and crime: Sub-sample of flood-exposed individuals

	(1)	*(2)*	*(3)*
Dependent variables	*Experienced theft*	*Physical attack*	*Fear crime*
Flood50_before	-0.006	-0.014	0.018
	(0.020)	(0.015)	(0.027)
Flood50_after	-0.094**	-0.065**	-0.105**
	(0.037)	(0.028)	(0.046)
Difference in Differences	0.089	0.050	0.123
F-test: Flood50_before – Flood50_after = 0	7.241	4.340	10.574
P-value	0.007	0.038	0.001
Mean of dep variable	0.310	0.120	0.471
Sample size	7,138	7,127	7,122
R-squared	0.021	0.028	0.054

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

Table A29 Natural disasters and crime: Controlling for socio-economic background

	(1)	*(2)*	*(3)*
Dependent variables	*Experienced theft*	*Physical attack*	*Fear crime*
Exposed50_before	-0.006	-0.009	0.012
	(0.022)	(0.016)	(0.029)
Exposed50_after	-0.097***	-0.063**	-0.112**
	(0.037)	(0.029)	(0.046)
Unemployment	0.009	0.008	0.056
	(0.012)	(0.009)	(0.014)
Primary education	-0.051*	-0.028	-0.015
	(0.030)	(0.020)	(0.033)
Secondary education	-0.029	-0.029	-0.005
	(0.029)	(0.021)	(0.035)
Tertiary education	-0.023	-0.032	0.005
	(0.032)	(0.023)	(0.037)
Wealth (one asset)	-0.012	-0.019	0.005
	(0.018)	(0.013)	(0.018)
Wealth (two assets)	0.013	-0.012	-0.003
	(0.019)	(0.014)	(0.021)
Wealth (three assets)	-0.033	-0.020	-0.028
	(0.026)	(0.020)	(0.025)
Difference in Differences	0.091	0.054	0.124
F-test: Exposed50_before – Exposed50_after = 0	7.815	4.932	11.480
P-value	0.005	0.027	0.001
Mean of dep variable	0.309	0.120	0.471
Sample size	7,110	7,099	7,094
R-squared	0.023	0.030	0.057

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region and year fixed effects, as well as additional controls for unemployment, education dummies, and wealth dummies. Omitted categories include no formal education and wealth (no assets). The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

Table A30 Natural disasters and crime: Analysis excluding individuals with no disaster exposure

	(1)	*(2)*	*(3)*
Dependent variables	*Experienced theft*	*Physical attack*	*Fear crime*
Exposed50_before	0.092***	0.056**	0.125***
	(0.033)	(0.025)	(0.037)
Mean of dep variable	0.309	0.121	0.475
Sample size	6,225	6,214	6,214
R-squared	0.018	0.026	0.052

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region, and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

Table A31 Natural disasters and crime: Employing alternative temporal exposure cut-offs

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Dependent variables	*Experienced theft*		*Physical attack*		*Fear crime*	
Temporal exposure	*5-year*	*10-year*	*5-year*	*10-year*	*5-year*	*10-year*
Exposed50_before	-0.017	-0.006	-0.033*	-0.021	-0.031	0.009
	(0.025)	(0.018)	(0.019)	(0.014)	(0.028)	(0.023)
Exposed50_after	-0.103***	-0.095***	-0.077***	-0.072***	-0.172***	-0.115***
	(0.038)	(0.036)	(0.025)	(0.027)	(0.042)	(0.042)
Difference in Differences	0.086	0.088	0.044	0.051	0.140	0.123
F-test: Exposed50_before – Exposed50_after = 0	4.307	7.023	2.602	4.343	10.764	10.971
P-value	0.039	0.008	0.108	0.038	0.001	0.001
Mean of dep variable	0.310	0.310	0.120	0.120	0.471	0.471
Sample size	7,138	7,138	7,127	7,127	7,122	7,122
R-squared	0.021	0.021	0.029	0.029	0.057	0.056

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables.

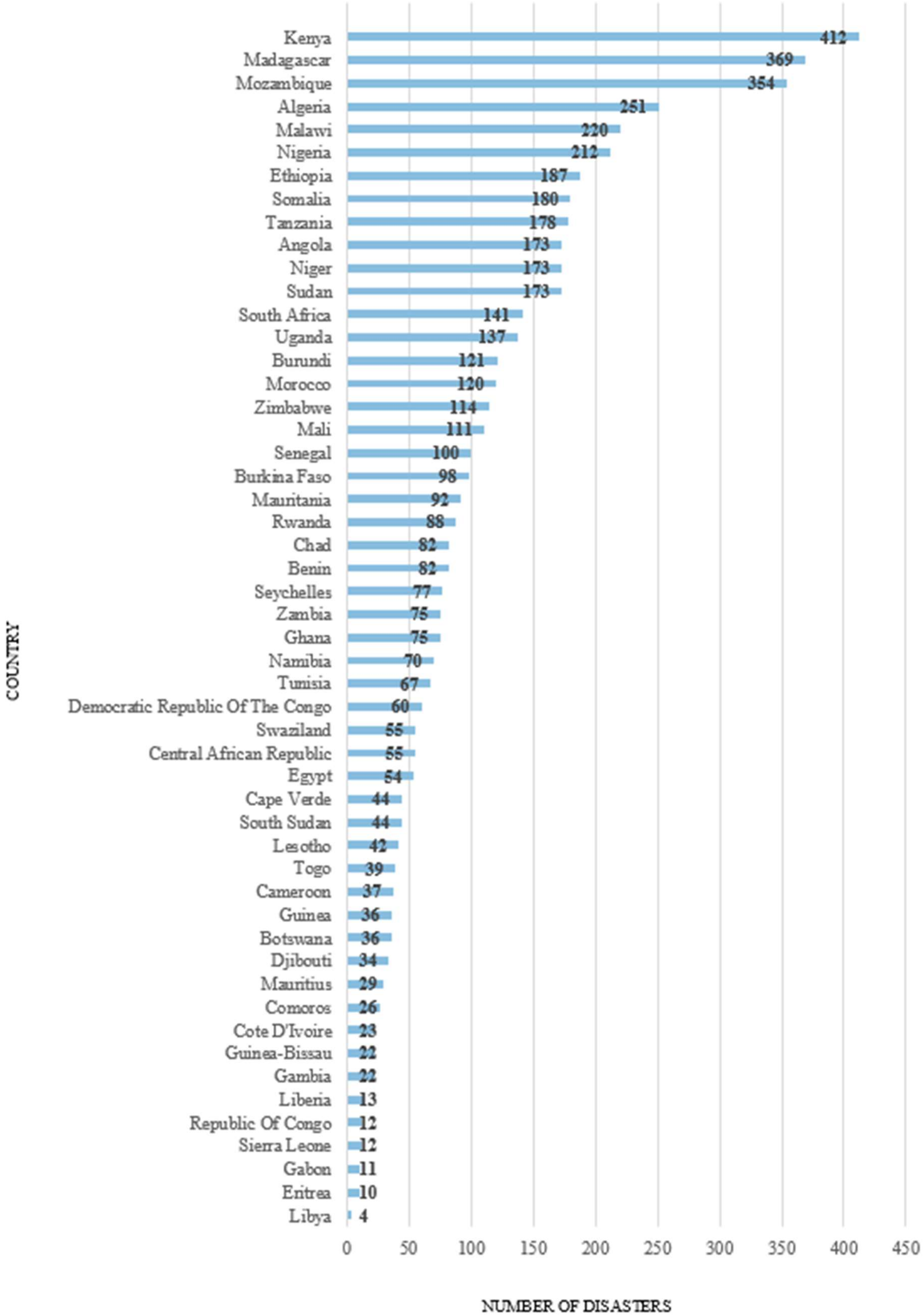
Table A32 Natural disasters and crime: Employing alternative spatial exposure cut-offs

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Dependent variables	*10km*	*20km*	*30km*	*40km*	*50km*	*60km*	*70km*	*80km*	*90km*	*100km*
Experienced theft										
Exposed_before	0.003	-0.007	-0.009	-0.010	-0.006	-0.010	-0.003	0.015	0.016	0.033
	(0.018)	(0.017)	(0.020)	(0.020)	(0.022)	(0.021)	(0.021)	(0.023)	(0.024)	(0.025)
Exposed_after	-0.054	-0.053**	-0.041	-0.061*	-0.095**	-0.120**	-0.122**	-0.099*	-0.095	-0.053
	(0.047)	(0.032)	(0.035)	(0.035)	(0.038)	(0.052)	(0.057)	(0.051)	(0.060)	(0.066)
Difference in Differences	0.057	0.048	0.031	0.052	0.089	0.110	0.120	0.115	0.112	0.086
F-test: Exposed_before – Exposed_after = 0	1.415	2.003	0.752	2.439	7.066	5.318	5.128	6.589	4.376	2.190
P-value	0.235	0.158	0.386	0.119	0.008	0.022	0.024	0.011	0.037	0.140
Mean of dep variable	0.310	0.310	0.310	0.310	0.310	0.310	0.310	0.310	0.310	0.310
Sample size	7,138	7,138	7,138	7,138	7,138	7,138	7,138	7,138	7,138	7,138
R-squared	0.020	0.020	0.020	0.020	0.021	0.021	0.021	0.021	0.021	0.021
Physical attack										
Exposed_before	0.007	0.001	0.001	0.001	-0.010	-0.008	-0.003	0.002	0.009	0.025
	(0.012)	(0.013)	(0.015)	(0.015)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Exposed_after	-0.047	-0.057***	-0.055***	-0.054**	-0.063**	-0.068*	-0.058	-0.066*	-0.051	-0.020
	(0.029)	(0.019)	(0.021)	(0.023)	(0.029)	(0.039)	(0.045)	(0.038)	(0.043)	(0.050)
Difference in Differences	0.054	0.058	0.056	0.055	0.053	0.060	0.056	0.067	0.060	0.045
F-test: Exposed_before – Exposed_after = 0	3.349	10.003	7.546	8.473	4.767	2.913	1.819	4.125	2.327	1.016

P-value	0.068	0.002	0.006	0.004	0.029	0.089	0.178	0.043	0.128	0.314
Mean of dep variable	0.120	0.120	0.120	0.120	0.120	0.120	0.120	0.120	0.120	0.120
Sample size	7,127	7,127	7,127	7,127	7,127	7,127	7,127	7,127	7,127	7,127
R-squared	0.028	0.029	0.029	0.029	0.028	0.028	0.028	0.028	0.028	0.028
Fear crime										
Exposed_before	0.005	-0.013	-0.025	-0.009	0.010	-0.010	-0.001	-0.013	-0.004	0.035
	(0.023)	(0.023)	(0.027)	(0.028)	(0.029)	(0.030)	(0.029)	(0.028)	(0.028)	(0.029)
Exposed_after	-0.083	-0.092**	-0.085**	-0.086*	-0.113**	-0.177***	-0.186***	-0.167***	-0.187***	-0.123*
	(0.051)	(0.037)	(0.040)	(0.045)	(0.047)	(0.060)	(0.058)	(0.053)	(0.058)	(0.066)
Difference in Differences	0.089	0.080	0.060	0.077	0.123	0.167	0.185	0.154	0.182	0.158
F-test: Exposed_before – Exposed_after = 0	2.920	5.016	2.493	4.054	11.199	9.910	14.100	11.885	13.666	7.804
P-value	0.088	0.026	0.115	0.045	0.001	0.002	0.001	0.001	0.001	0.005
Mean of dep variable	0.471	0.471	0.471	0.471	0.471	0.471	0.471	0.471	0.471	0.471
Sample size	7,122	7,122	7,122	7,122	7,122	7,122	7,122	7,122	7,122	7,122
R-squared	0.054	0.055	0.055	0.055	0.056	0.056	0.056	0.056	0.056	0.056

Note: *** p < .01, **p < .05, * p < .1. Standard errors, clustered at the PSU level, are in parenthesis. All regressions include baseline controls (age, age squared, gender, and urban dummy), sub-national region and year fixed effects. The sample includes Kenyan Afrobarometer rounds 2 – 6 for all variables. *Exposed_before* and *Exposed_after* in Table A7 are generated based on the spatial restrictions indicated by each model in 10-kilometre increments from 10km to 100km.

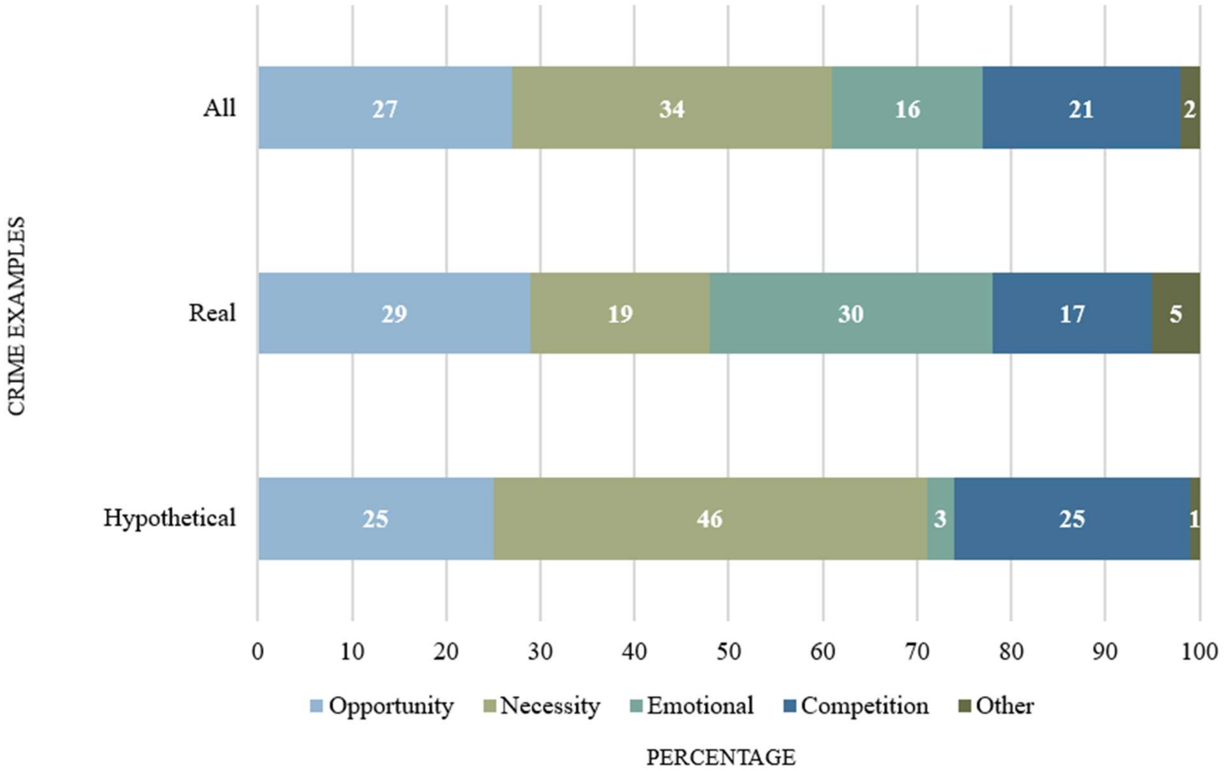
Figure A7: Number of disasters per country in GDIS 1960 – 2018, African countries



Note: Figure A1 captures all African countries that appear in GDIS. Kenya records the highest number of disasters across this period for all African countries. Kenya's earliest record of disaster in GDIS is 1979.

4.8. Appendix B: Natural disasters and crime: Evidence based on primary data from Baringo, Kenya

Figure B1: Crime reasoning by real-life versus hypothetical crime scenarios



Note: The figure is based on the pool dataset of real-life and hypothetical crime scenarios with a combined sample size of 429. For both crime examples, respondents provided open-ended qualitative answers and responses were coded by the research team afterwards. Categories were developed during coding to encompass all provided options by respondents. For real crime examples, respondents were asked "Why do you think the individual did it?". For hypothetical crime examples, respondents were asked one of the following depending on the crime type: "Why do you think a natural disaster would make it easier for individuals to steal?", "Why do you think a natural disaster would make assaults more frequent?". "Why do you think a natural disaster would increase property crime?", "Why do you think a natural disaster would make it easier for ethnically motivated crime to occur?". All answers provided by respondents fell under one of the five categories.

Primary Data – Questionnaire and Codebook

Variable names are in red italics next to the relevant questions.

Basic demographics

1. Gender of respondent (*gender*)
Coding: 0 = Female, 1 = Male, -1 = No Answer

2. How old are you? (*age*)
Coding: 18 – 99, -1 = No Answer

3. What is your marital status? (*marital*)
Coding: 0 = Single, 1 = Married, 2 = Divorced, 3 = Other, -1 = No Answer

4. How many children do you have? (*children*)
Coding: Numeric, -1 = No Answer

5. What is your religion, if any? (*religion*)
Coding: 0 = Christian, 1 = Traditional African Spiritualist, 2 = Other, -1 = No Answer

6. What ethnic group are you from? (*ethnicity*)
Coding: 1 = Njemps, 2 = Turgen, 3 = Pokot, 4 = Other, -1 = No Answer

7. What is the highest level of school that you have completed? (*education*)
Coding: 0 = No Schooling, 1 = Primary, 2 = Secondary, 3 = Tertiary, 4 = Other, -1 = No Answer)

8. Is the head of your household currently employed? (*employment*)
Coding: 0 = No, 1 = Yes, -1 = No Answer

9. Select your main source of household income: (*income*)
Coding: 0 = Unemployed, 1 = Agriculture, 2 = Self Employed, 3 = Cash Employment, 4 = Remittances, 5 = Other, -1 = No Answer

10. Have you been impacted by the Baringo floods in any of the following ways?

a) Damaged property [*sev_prop*] (Not at all/Moderately/Severely/No Answer)
b) Loss of income [*sev_income*] (Not at all/Moderately/Severely/No Answer)
c) Loss of job [*sev_job*] (Not at all/Moderately/Severely/No Answer)
d) Psychological distress [*sev_psych*] (Not at all/Moderately/Severely/No Answer)
e) Loss of livestock [*sev_livestock*] (Not at all/Moderately/Severely/No Answer)
f) Compromised land quality [*sev_land*] (Not at all/Moderately/Severely/No Answer)
g) Loss of assets [*sev_asset*] (Not at all/Moderately/Severely/No Answer)

Coding: 0 = Not at all, 1 = Moderately, 2 = Severely, -1 = No Answer

11. Has the frequency of the following types of crime or violence changed since the Baringo floods?

a) Theft [*theft*] (Decreased/Stayed the same/Increased/No Answer)
b) Assault [*assault*] (Decreased/Stayed the same/Increased/No Answer)
c) Property crime [*property*] (Decreased/Stayed the same/Increased/No Answer)
d) Ethnically motivated crime and violence [*ethnic*] (Decreased/Stayed the same/Increased/No Answer)

Coding: 0 = Decreased, 1 = Stayed the same, 2 = Increased, -1 = No Answer

Hypothetical crime scenarios

We will now describe to you scenarios of crimes that might occur in your community after exposure to a natural disaster [flood]. We will then ask you what you think and feel about these crimes. Honesty is encouraged and these answers are for research purposes only, your identity will remain anonymous.

Scenario 1 (theft) [*crime type*]

12. Ok, let me start with the first scenario. After a flooding, individuals were each given bags of rice/food by the State. One household discovered that a 35-year-old male broke into their house and stole their food supplies. Other neighbours also reported that their food had gone missing.

    (a) How would you react if something similar happened in your community? (*response*)

    Coding: 1 = Deontological, 2 = Consequentialist, 3 = Empathy, 4 = Other, -1 = No Answer

    (b) Why do you think a natural disaster would make it easier for individuals to steal? (*cause*)

    Coding: 1 = Creates Opportunity, 2 = Creates Vulnerability/Necessity, 3 = Desire/Revenge/Greed/Power, 4 = Competition for Resources, 5 = It Would Not, -1 = No Answer

    (c) Do you think victims of a natural disaster may have more motivation to steal? (*motivation*)

    Coding: 0 = No, 1 = Yes, -1 = No Answer

    (d) You find out the thief stole the food to feed their children, does this change how you feel? (*chng_resp*)

    Coding: 0 = No, 1 = Yes, -1 = No Answer

Scenario 2 (assault) [*crime type*]

13. Now here is the second scenario. After being forced to move after storm damage, a community sets up in a new area. Individuals no longer feel they have the security of their usual community structure. One evening, a woman is attacked and left with visible bruising along her arms. The woman reports this would not have happened if they did not move.

    (a) How would you react if something similar happened in your community? (*response*)

Coding: 1 = Deontological, 2 = Consequentialist, 3 = Empathy, 4 = Other, -1 = No Answer

(b) Why do you think a natural disaster would make assaults more frequent? (*cause*)

Coding: 1 = Creates Opportunity, 2 = Creates Vulnerability/Necessity, 3 = Desire/Revenge/Greed/Power, 4 = Competition for Resources, 5 = It Would Not, -1 = No Answer

(c) Do you think victims of a natural disaster have more reason to assault others? (*motivation*)

Coding: 0 = No, 1 = Yes, -1 = No Answer

(d) You find out the victim was attacked over money, does this change how you feel? (*chng_resp*)

Coding: 0 = No, 1 = Yes, -1 = No Answer

Scenario 3 (property crime) [*crime type*]

14. Here is the third scenario. A heatwave has struck a small community and forced members of that community to shelter together in a community building where there is water and food available. Whilst sheltering, one family's home is vandalised and significantly damaged. The family believes it was done by another family they previously had land conflict with, but there is no way to prove it.

(a) How would you react if something similar happened in your community? (*response*)

Coding: 1 = Deontological, 2 = Consequentialist, 3 = Empathy, 4 = Other, 1 = No Answer

(b) Why do you think a natural disaster would increase property crime? (*cause*)

Coding: 1 = Creates Opportunity, 2 = Creates Vulnerability/Necessity, 3 = Desire/Revenge/Greed/Power, 4 = Competition for Resources, 5 = It Would Not, -1 = No Answer

(c) Do you think victims of a natural disaster may have more motivation to commit crime? (*motivation*)

Coding: 0 = No, 1 = Yes, -1 = No Answer

(d) You find out the home was vandalised because the family stole livestock, does this change how you feel? (*chng_resp*)

Coding: 0 = No, 1 = Yes, -1 = No Answer

<u>Scenario 4 (ethnically motivated crime and violence)</u> [*crime type*]

15. Now here is the last scenario. Two different ethnic groups/communities need to relocate due to a drought drying up all their natural water sources. Both communities move next to the same lake. Two families, one from each community, try to occupy the same plot of land as it is good for crops. This causes conflict and eventually one of the family members is assaulted. So far, the local police have done nothing, but other members of the community think they know who assaulted the individual.

    (a) How would you react if something similar happened in your community? (*response*)

    Coding: 1 = Deontological, 2 = Consequentialist, 3 = Empathy, 4 = Other, -1 = No Answer

    (b) Why do you think a natural disaster would make it easier for ethnically motivated crime to occur? (*cause*)

    Coding: 1 = Creates Opportunity, 2 = Creates Vulnerability/Necessity, 3 = Desire/Revenge/Greed/Power, 4 = Competition for Resources, 5 = It Would Not, -1 = No Answer

    (c) Do you think victims of a natural disaster have more motivation for ethnically charged crime? (*motivation*)

    Coding: 0 = No, 1 = Yes, -1 = No Answer

    (d) You find out that the assaulted individual was contaminating/poisoning the land so no one could use it for crops, does this change how you feel? (*chng_resp*)

    Coding: 0 = No, 1 = Yes, -1 = No Answer

Specific cases of crime and conflict.

16. Have any crimes occurred since the Baringo floods in your community? (asked twice)

a) What happened? (*ex_type*)

   Coding: 1 = Theft, 2 = Physical Assault, 3 = Sexual Assault, 4 = Property Crime, 5 = Ethnically Motivated Crime, 6 = Land Conflict, 7 = Other, -1 = No Answer

b) Why do you think the individual did it? (*reasoning*)

   Coding: 1 = Opportunity, 2 = Necessity, 3 = Desire/Revenge/Greed/Power, 4 = Competition for Resources, 5 = Other, -1 = No Answer

c) Do you think this action or reasoning is justifiable? Why? (*justifiable*)

   Coding: 0 = No, 1 = Yes, -1 = No Answer

d) What, if any, are the benefits to committing a crime like this? (*benefit*)

   Coding: 0 = No Benefits, 1 = Reward, 2 = Survival, 3 = Benefits are outweighed by punishment, -1 = No Answer

e) What is the probability of being caught doing this in your community? (*probability*)

   Coding: 0 = Very Low, 1 = Low, 2 = Likely, 3 = Very Likely, -1 = No Answer

f) Do you think the punishment for this crime prevents people from doing it? Why? (*punishment*)

   Coding: 0 = No, 1 = Yes, -1 = No Answer

g) How often does this type of crime happen in your community? (*often*)

   Coding: 0 = Never, 1 = Infrequent, 2 = Sometimes, 3 = Frequently, -1 = No Answer

h) When thinking about the period since the Baringo floods, has the frequency of this type of crime changed? Why? (*frequency*)

   Coding: 0 = Yes, Decreased, 1 = No, 2 = Yes, Increased, -1 = No Answer

Moral and psychological reasoning

Now, I would like you to think of the decisions individuals make before committing a crime and whether you believe they are rationally or emotionally motivated.

17. Do you think rational thought or emotion triggers an individual's choice to steal? Why? (*mpr1*)
18. Do you think rational thought or emotion triggers an individual's choice to commit assault? Why? (*mpr2*)
19. Do you think rational thought or emotion triggers an individual's choice to perform property crime? Why? (*mpr3*)
20. Do you think rational thought or emotion triggers an individual's choice to commit ethnically charged crime? Why? (*mpr4*)

Coding: 0 = Neither, 1 = Rational, 2 = Equal parts rational and emotional, 3 = Emotional, -1 = No Answer

System one decision making (heuristics)

Now I am going to ask you a series of [yes/no] questions that must be answered within 10 seconds. No answer within this time period will be recorded as 'No Response'.

21. Do you think individuals would commit more crimes if there was less authority? (*H12*)
22. Do you think natural disasters create an opportunity for more crime? (*H13*)
23. Do you think a corrupt government encourages more crime? (*H14*)
24. Do you think your local government is currently corrupt? (*H15*)
25. Do you think men have more to gain by committing a crime? (*H16*)
26. Do you think the benefits of committing a crime are increased after a disaster? (*H17*)
27. Do you think individuals would commit more serious crimes if the reward were larger? (*H18*)
28. Do you think individuals see crime as a way of regaining what they lost during a disaster? (*H19*)

    Coding: 0 = No, 1 = Yes, -1 = No Answer

5. Conclusion

This thesis provides an analysis of the social impacts of natural disasters in Africa, including individual coping responses, generalised and other dimensions of trust, and crime. Insights into these social impacts are achieved based on a rigorous analysis of geocoded data from the Afrobarometer social survey and GDIS (Rosvold and Halvard, 2021), complemented with primary collected data in Kenya in the final chapter. The findings identified across all three essays contributes significant evidence that there are substantial social impacts that arise from exposure to natural disasters in developing country contexts.

The first essay, "Coping collectively: Responses to natural disasters in Africa", exploits a spatial-temporal difference-in-differences estimation strategy comparing individuals exposed to a disaster with those at risk to assess the close-to-causal effects of disaster exposure on individual coping responses. The results for the first essay show individuals who are exposed to a disaster prior to interview self-report worse living conditions and greater economic vulnerabilities as well as show an increased perception of poor governmental performance and an increased perception of corruption amongst government institutions and officials. We then explore the coping responses of individuals under such circumstances and demonstrate that individuals exposed to a disaster prior to interview are more likely to engage in collective action by participating in, and acting as, a group. Disaster-exposed individuals are less likely to contact government officials and despite increased interest in public affairs, they are less likely to protest or translate that interest into political engagement. This result is consistent with findings from Bangladesh (Islam and Nguyen, 2018) and Indonesia (Kumar, 2017) that local collective action is an essential recovery mechanism in developing contexts.

The second essay, "Trust a few: Natural disasters and the disruption of trust in Africa", uses the *impressionable years hypothesis* to explore how compounded disaster exposure throughout early adulthood (ages 18 – 25) might disrupt the formation of generalised and other dimensions of trust. This essay uses geospatial disaster data to compound disaster exposure over the impressionable years to determine whether the frequency of disaster shocks interrupts an individual's formation of generalised trust. Results for the second essay show that increased disaster frequency throughout the impressionable years is associated with reduced generalised trust. We further analyse whether this effect extends to other dimensions of trust, notably other strands of interpersonal and institutional trust. The results indicate more frequent disaster exposure also reduces trust in other dimensions of interpersonal trust. Similarly, the results also demonstrate a reduced trust in the president and the electoral commission. By highlighting that the observed effect is not isolated to generalised trust, this essay shows disaster exposure has a significant effect on trust as a whole. These findings corroborate those found in Bangladesh (Rahman et al. 2020) and Chile (Fleming et al. 2014) that disasters reduce interpersonal trust and reciprocity. Additionally, the second essay highlights that the attitudes formed throughout the impressionable years period are carried throughout adulthood.

The third essay, "Crimes of the current: Natural disasters and crime in Kenya", studies the impact of disaster exposure on crime incidence and the transmission mechanisms. Using a mixed-methods approach, this essay employs a similar cross-sectional difference-in-differences approach to the first essay to study the relationship between natural disaster exposure and crime in Kenya, coupled with additional qualitative evidence from a case study in Baringo, Kenya, to study the mechanisms. The quantitative results for the third essay show that individuals who are exposed to disaster before interview were more likely to have experienced instances of crime (theft and/or assault) and to fear crime in their household than those exposed after interview. The essay additionally explores the results of semi-structured interviews conducted in Baringo, Kenya using both hypothetical and real crime scenarios to uncover the mechanisms driving increases in crime. Results show that respondents still maintain a perception of high costs associated with to participating in crime, with high perceived levels of capture and punishment. They also indicate, however, that disaster circumstance does increase the benefits to crime and evidence suggests that crimes are motivated by various considerations, whether they be offsetting resource scarcity, balancing economic vulnerabilities, or resolving underlying circumstantial or ethnic frustrations through expressive violence. These insights add valuable understanding to the literature that has produced mixed evidence on the link between natural disaster exposure and crime, hardly engaging with underlying mechanisms (Zahran et al. 2009; Curtis and Mills, 2011; Kwanga et al. 2017; Purnama et al. 2020).

Many of the social impacts observed in these essays are symptomatic of unstable or unreliable institutions that cannot, or do not, support the needs of their communities. Lack of government response or intervention after a disaster leads to resource windfalls and conflict around the means to survive. These issues fall particularly hard in communities with a history of ethnic and pastoral conflict, as observed in many African nations. These experiences in turn breed attitudes of distrust between communities and disengagement from institutional bodies.

Despite this, there remains a strong level of goodwill among community members in their response to disasters reflected in collective action. Institutions, whether national governments or Non-governmental organisations, could leverage this grassroots collective action in assisting in disaster recovery to not only speed up the response time, but to offset the anti-social behaviours that may emerge from a lack of intervention.

This thesis and essays are by no means conclusive on the subject of natural disasters in Africa and there are great opportunities to extend the research on these topics in broader and more inclusive ways. For example, information in the Afrobarometer survey on collective action is limited to how individuals engage with government institutions, however we are limited in our ability to understand the nature of collective action, as well as its outcomes. In particular, future research into how individuals respond through engagement with non-governmental organisations and whether the grassroots collective action that emerges is leveraged by those organisations would be fruitful.

Additionally, many of the disasters used in this thesis are floods, as due to the irregular timing of how droughts are recorded, we weren't able to study them in our difference-in-differences approach that is reliant on precise identification of timing of disasters. Droughts are, however, an ongoing issue for Africa impacting agricultural livelihoods and there could be further research done into how droughts specifically impact some of these social attitudes and behaviours taking a different estimation approach.

There is also great potential to further explore institutional trust in Africa more closely. Much of the literature discourse focuses on ethnic or interpersonal trust, however depending on the set-up of governmental processes, often institutional positions of power are held by specific ethnic groups within regions or nations. How those dynamics influence the individuals engagement with the institution, or the division of resources in disaster management, present interesting potential fields of study.

Lastly, as the third essay focuses on a case study from Kenya, there is obvious scope to extend this research to other countries. The mixed-methods approach of the study may be particularly helpful in gaining in-depth understanding of the behaviours post-disaster in other settings.

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