Working Paper UGA-21096 December 2022

The long-term welfare impacts of natural disasters: Evidence from Ugandan landslides

Travis Baseler
Jakob Hennig

DIRECTED BY

FUNDED BY

The Long-Term Welfare Impacts of Natural Disasters: Evidence from Ugandan Landslides*

Travis Baseler† Jakob Hennig‡

December 13, 2022

Abstract

Natural disasters forcibly displace millions of people a year. We study the economic impacts of displacement in Uganda, where landslides have forced an estimated 65,000 people from their homes. We combine administrative and survey data from affected and nearby households with a geological model of landslide risk to identify causal impacts. Landslides lead to substantial increases in long-term displacement and migration, and affected households are significantly worse off years after the event along several measures of welfare including economic and psychological health. Displacement outside the village and limited aid to cover damages appear to explain the negative welfare effects.

JEL Classifications: J61, O15, Q54

Keywords: displacement, natural disasters, climate refugees, forced migration

1 Introduction

Between 2008 and 2018, around 265 million people were displaced by natural disasters such as floods, storms, earthquakes, tsunamis, and landslides. Climate change threatens to increase the frequency and severity of these disasters (IDMC, 2019). There is a clear need for

*We thank the International Research Consortium, and especially Dr. Daniel Kibuuka Musoke and Aidah Nakitende, for their diligent work coordinating and collecting field data, and Ande Shen for excellent research assistance. We also thank the International Growth Centre for funding this study. This study has received approval from the Institutional Review Board (IRB) at the University of Rochester (Study 6572), the Mildmay Uganda Research Ethics Committee (Study 2021-86), and the Uganda National Council for Science and Technology (Study SS1263ES).

†University of Rochester, travis.baseler@rochester.edu

‡The World Bank, jhennig@worldbank.org

governments and humanitarian organizations to understand the economic impacts of natural disaster displacement (henceforth, simply *displacement*) on affected individuals, and what factors contribute to successful resettlement. However, the nature of displacement makes estimating these impacts difficult, especially in developing countries where the vast majority of at-risk individuals reside. First, exposure to natural disasters is likely to be correlated with potential economic outcomes, as richer or more mobile households sort away from high-risk areas. Second, displacement itself makes data collection much more difficult, as the affected population becomes dispersed. These challenges have led to a paucity of such estimates in the economic literature, especially in developing countries.

This paper studies the economic impacts of displacement by landslides in Eastern Uganda, where 300,000 people have been affected, and 65,000 displaced, by recent landslides (OCHA, 2019). Climate change and an increased frequency of heavy rains is an important factor in these disasters (World Bank Group, 2020). We combine administrative lists of households in affected regions with a household survey we conducted in 2022 with affected and nearby households, regardless of their current location. This allows us to estimate the average impact of landslides on the complete set of affected households, which may be very different than the impact on the set of households that remain, especially in settings with high rates of displacement. We use exact information on the path of the landslide and households' pre-landslide locations to identify the causal impact of the disaster. Applying a risk model developed in the geomorphology literature specifically for our study region (Claessens et al., 2007), we show that within an affected area, households exposed to greater landslide risk do not systematically differ from those in less risky locations. Moreover, the risk measure for households located in or close to the ex-post path of the landslide was not elevated in comparison to their neighbors. We therefore argue that while the overall risk of landslides in the area can be known, the exact path of the slide introduces exogenous variation in landslide damage.

Landslide victims—defined as those residing within 50 meters of the landslide path—are 50 percentage points (pp) more likely to be displaced outside their home village. Almost all remain in rural locations. By the time of the survey in 2022, about two-thirds of these have returned to their home village. The landslide also increases rural-to-urban migration of individuals within the household, which persists in the long run. The increase in migration is concentrated in households without urban migrants at the time of the landslide, suggesting that new and existing migrants are substitute coping strategies. In 2022, between 2 and 12 years after the landslide events, affected households are substantially worse off along several welfare measures: they live in lower-quality housing and report lower financial and mental health. Welfare impacts—both cross-sectionally and compared to retrospective pre-landslide levels—are much worse for households that were displaced outside their home villages. These negative impacts are mitigated for households with family living in big cities at the time of the landslide, and for households whose landslide damage was mostly covered by external aid.

Overall, our results indicate that natural disasters can have substantial negative long-run impacts on affected households, especially on those that are displaced from their homes. This finding is in stark contrast to estimates from developed countries, which often find positive long-run impacts of displacement on income and human capital (Sacerdote, 2012, Deryugina et al., 2018, Nakamura et al., 2021), possibly by disrupting locational ties that have adverse economic consequences. A number of studies in low-income settings have also found positive long-run economic impacts of natural disaster (Gignoux and Menéndez, 2016, Heger and Neumayer, 2019), potentially driven by subsequent aid receipts. The contrast between our findings and others in the literature thus suggests that the positive impacts of natural disaster may be contained to contexts in which households are not forced to leave their homes, or in which aid or other forms of insurance can cover financial losses.

This paper contributes to the literature studying the economic impacts of natural disasters. Nakamura et al. (2021) study a volcanic eruption which displaced households out of a high-income fishing village in Iceland. The authors find that displaced households are better-educated and earn much more, with results concentrated in younger individuals, for whom high moving costs may preclude optimizing over locations based on comparative advantage. Deryugina et al. (2018) study the impact of Hurricane Katrina on income, and find positive long-run effects, with the largest changes observed among households who moved away from New Orleans permanently. Sacerdote (2012) studies the impact of Hurricanes Katrina and Rita on the test scores of displaced students. After an initial drop in scores, impacted students' scores are higher by the third year following displacement.

The literature studying natural disaster impacts in developing economies finds more mixed results. At the macroeconomic level, Noy (2009) finds that less developed countries are less able to withstand shocks from natural disasters. Gignoux and Menéndez (2016) and Heger and Neumayer (2019) study the long-run effects of earthquakes and tsunami, respectively, in Indonesia. Both find positive long-run effects on economic output, driven at least partly by the substantial external aid receipts that followed the disasters. Gröger and Zylberberg (2016) study household coping responses to a typhoon in Vietnam using longitudinal household data, and find that households cope with the negative shock to income with increased remittance receipts from existing migrants, and by sending new migrants to urban areas. However, both Gignoux and Menéndez (2016) and Gröger and Zylberberg (2016) study settings in which displacement of the entire household was rare or nonexistent. Our paper is the first we are aware of to use household data to study the impact of natural disaster in a developing country that involved substantial household displacement.

The literature on natural disaster displacement sits within a broader literature on forced migration, including by conflict or persecution. Chiovelli et al. (2021) study the impact of forced displacement during the Mozambican civil war on human, social, and civic capital using census data. The authors find that displacement generates an increase in educational investment, with the greatest effect observed in rural-urban movers. However, the displaced have lower social and civic capital and worse mental health compared to the urban-born. Cortes (2004), Gray et al. (2014), Chin and Cortes (2015), Aksoy and Poutvaara (2021) and Abramitzky et al. (2022) study the selection of refugees compared to other immigrants or to non-immigrants, but do not estimate the impact of displacement on the displaced. Cattaneo and Peri (2016) study the impact of rising temperatures on migration, but also do not estimate impacts on the displaced.[1] A major difficulty in extrapolating the displacement impacts from conflict to a natural disaster context is that the non-displaced in a conflict setting often remain in an environment of violence or instability, implying that displacement effects relative to a conflict-free counterfactual are difficult to estimate.

This paper proceeds as follows. Section 2 describes our setting. Section 3 details our study design, including our sampling frame, identification strategy, and estimating equations. Section 4 presents results on landslide destruction, effects on displacement and migration, effects on welfare, and discusses potential mechanisms. Section 5 concludes.

2 Background

Our study area is the Mt. Elgon region of Eastern Uganda, where most of the landslides and landslide-related deaths and displacement in Uganda have occurred.[2] Between 2010 and 2020, landslides resulted in at least 1,000 deaths in the region, and in tens of thousands of displacements.[3]

The main hot spot for these disasters is Bududa district, located at an average altitude of 1,300 meters around an extinct crater in the Mt. Elgon range. The volcanic soils and steep slopes of Bududa contribute to landslide risk, as do the increasing population density and crop cultivation (Knapen et al., 2006, Claessens et al., 2007). The primary economic activity is farming, especially of maize and bananas, and coffee as a cash crop (Akoyi and Maertens, 2018).

Despite international attention, humanitarian aid, and attempts by the Ugandan government to relocate victims and the at-risk population, landslide risks have only grown over time (Independent, 2020). These risks are closely related to climate change, in particular more frequent heavy rainfall events, which destabilize susceptible slopes (World Bank

[1] See Becker and Ferrara (2019) for a review of the forced migration literature.

[2] Another affected area is the Rwenzori range in Western Uganda.

[3] See OCHA (2019), Monitor (2019). As the sources note, the exact number of victims is hard to determine since many remain missing and unaccounted for.

Group, 2020). The number of landslides and floods has increased over the last 30 years, and is expected to increase further.

Bududa has frequently been the site of geological landslide risk assessments, for example in Claessens et al. (2007, 2013). The authors of these studies have generously provided us with their data and advice. Their dataset includes a 10-meter-by-10-meter grid of the elevation, slope, distance to the watershed, and soil type, as well as a landslide risk measure based on these features. The risk model in Claessens et al. (2007) (called LAPSUS-LS) is based on a mapping of 81 earlier landslides in the same region, which enabled the authors to determine the statistical relationship between geological features and landslide risk. The model output is a critical rainfall value, above which a plot would become unstable.

We use the LAPSUS-LS risk measure as a control variable in our main specifications. Importantly, the LAPSUS-LS variables and their geological inputs do not do not exhibit substantial differences between households originally located in the landslides' path, relative to their neighbors. This suggests that while geological features can predict the likelihood of a landslide for the village as a whole, it is more difficult to predict which part of the slope will become unstable.

3 Study Design

We estimate the impact of landslides on affected households by combining household surveys with geographic coordinates of the landslide paths and a geological model of risk taken from Claessens et al. (2007). As the nature of displacement makes relying on panel data infeasible—large-scale panels do not typically track the displaced over time, and the unpredictability of natural disasters usually makes pre-period data collection impossible—we rely on cross-sectional variation and compare affected to unaffected households within the same areas.

3.1 Site Identification and Data Collection

We worked together with local leaders with insight into recent landslide events to identify suitable sites for our study. These local leaders advised us on the sites of the largest landslides in the last 10 years, and shared lists of households that resided in villages in or near these sites at the time of the event. These lists form our study sample.

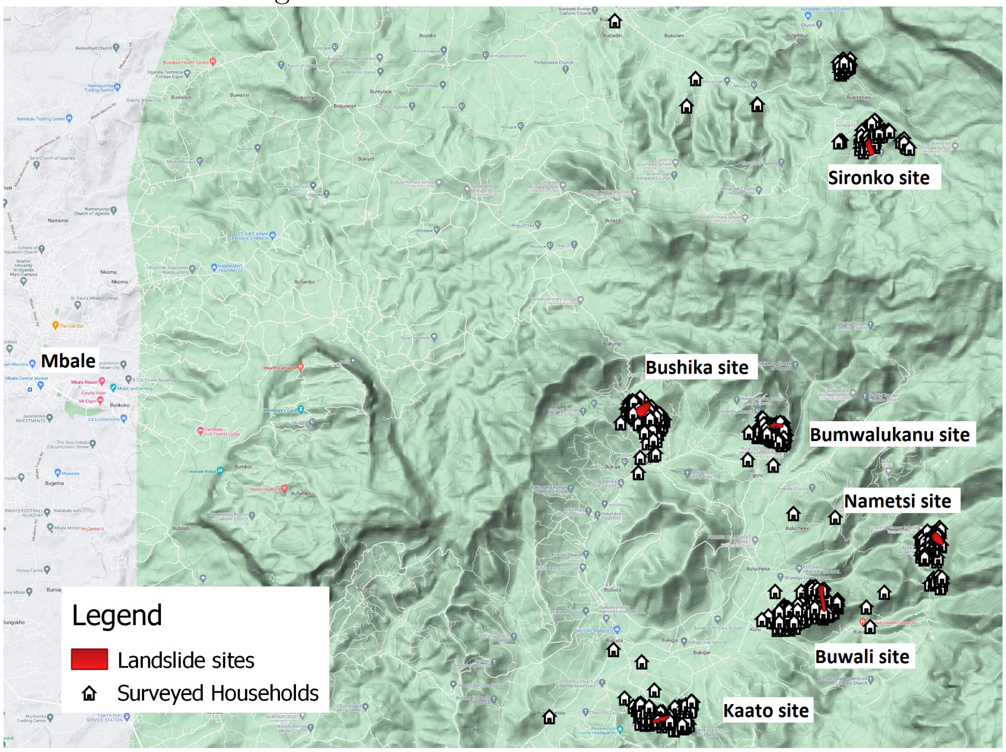
We decided to survey households from 6 sites: four in Bududa district, and one each in the neighboring Manafwa and Sironko districts. The Bududa sites include the large Nametsi landslide in 2010, discussed above, as well as an equally destructive event in Bumwalukani sub-county in 2012, and two more recent events. These are the 2019 landslides in Bushika and Buwali sub-county, which together killed close to 100 residents and displaced more than 1,000.[4] We also identified the site of a 2018 landslide in Kaato sub-county of Manafwa district, and of a 2017 landslide in Bufupa sub-county of the Sironko district. The location of these sites relative to the sub-regional capital of Mbale can be seen in Figure 1.

For each of these landslide sites, we established the extent of the survey perimeter, by identifying directly hit villages and neighboring villages which could serve as control areas. We largely limited the scope of the survey to the villages on the slopes where the landslide occurred, to have an ex-ante homogenous population of affected and unaffected households. Figure 2 shows these sites with the villages identified for our survey. It should be noted that there is relatively little clustering of dwellings, as farmers in this region work the fields directly surrounding there homestead, rather than living closely together in a village surrounded by fields. This increases the risk that some households will be hit by a landslide; clustering of dwellings in stable locations would be less risky.

We then worked with our local contacts to collect information on the households living in these survey areas before the landslide events. For this purpose, they accessed past registers of households living in the villages, available at the offices of local village leaders. We could therefore attempt a survey of the full population which lived in these affected and neighboring

[4] Establishing the exact number of victims is difficult due to conflicting reports.

Figure 1: Overview of Landslide Sites

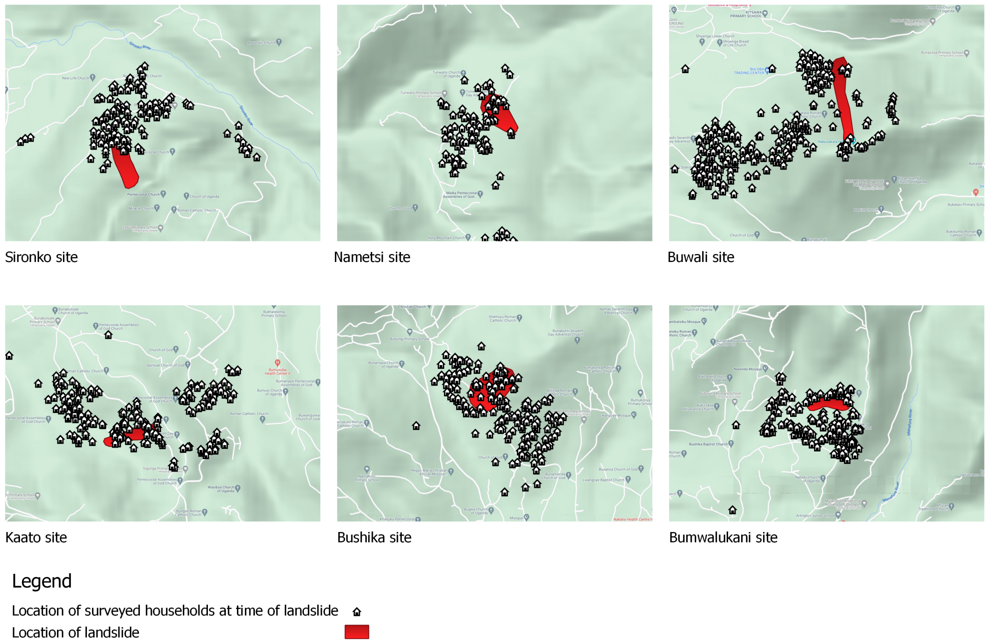


villages before the landslide event.

This process resulted in a master list of 1,046 households for the survey. Additionally, we asked our survey firm, the International Research Consortium, to conduct snowball sampling by enquiring about neighboring households not on the master list during their fieldwork. Through this process, only 29 households were added, which increases our confidence that the original master list based on pre-event population registers is reasonably complete.

From each of these households, IRC interviewed at a minimum the household head; in those cases were the household had split, they also interviewed the head of the new household when possible. Where no member of the new household could be contacted, we rely on information given by the original household head about their circumstances. We tracked households no longer residing in the village extensively using contact information obtained from neighbors or local leaders. Altogether, we were able to survey 91.3% of the households

Figure 2: Details of Landslide Sites



Notes: The maps illustrate the location of households at the time of the landslides as well as the exact landslide paths.

that resided in the affected areas at the time of the landslide.

3.2 Identifying Variation

Each landslide event corresponds to an affected "area" containing several villages. In our analysis we exploit variation in landslide exposure only within these affected areas by including a landslide-event fixed effect.

We used satellite images to trace the exact landslide paths, and verified these with our local contacts. For households still living in their original dwelling, the dwelling coordinates were recorded by the survey team during interviews. For households who had moved, the coordinates were recorded by our local contacts during subsequent field visits. These coordinates enable us to construct our main treatment variable, which captures whether a household was located in the path of the landslide, or within 50 meters (m) from it, before the event.

We include houses within the buffer of 50m to account for some imprecision in our coordinates, the possibility that destabilized ground close to the landslide path could damage buildings, and that households' pre-landslide locations were not always accessible by staff collecting GPS readings.[5] A buffer of 50m is our preferred definition because households within this distance are much more likely to self-report damage to their dwelling compared to households located slightly farther away. Our main results are robust to relying on self-reported landslide damage, and on removing the 50-meter buffer when categorizing households, as shown in Table A1.

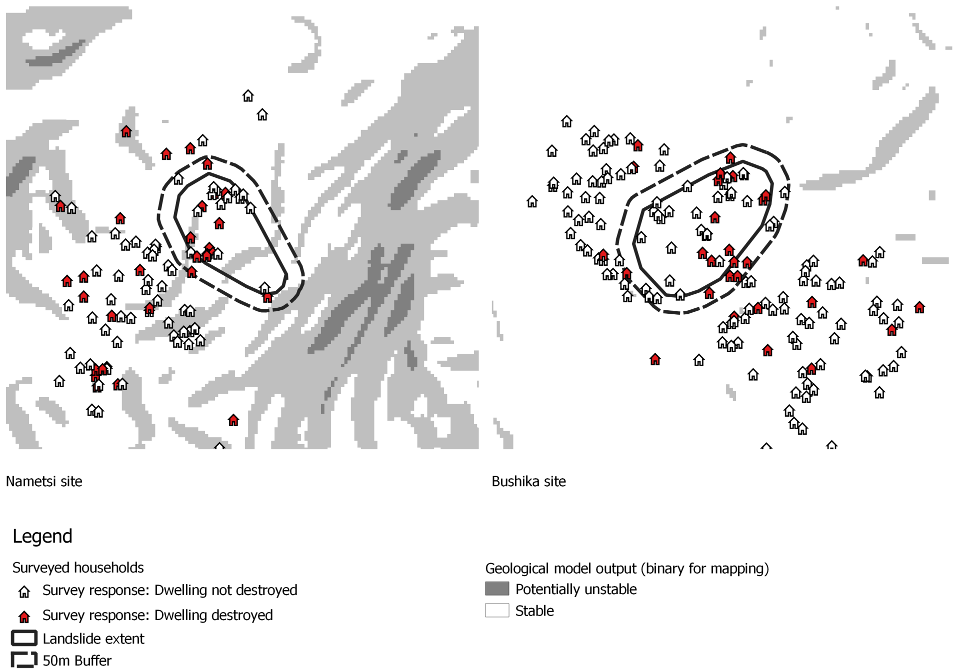
Figure 3 shows two of the landslide sites with this 50m buffer around them. Some of the dwellings mapped in the path of the landslide are classified as not destroyed, indicating that there is some measurement error, either from imprecise GPS readings or erroneous survey responses. However, as shown in Section 4.1, respondents with dwellings in or close to the landslide path are substantially more likely to report that their dwelling was completely destroyed during the event (39% versus 7%). This indicates that despite some measurement error, our measure of the landslide path is a good proxy for landslide damages.

The figure also shows the classification of grid points by the LAPSUS-LS geological landslide risk model. It provides visual confirmation that within sites, the direct path of the landslide is hard to predict, as the adjacent slopes have a very similar risk profile. This was also confirmed to us in interviews with local residents and leaders, who stressed that many more slopes appear unstable than experience a slide, and that the extent of a slide is difficult to predict from the slope's appearance.

In section 3.4, we provide additional evidence that the exact path of the landslide within an area introduces exogenous variation in landslide damage. It is not significantly related to either the ex-ante characteristics of the households in or near this path, or the ex-ante geological features and risk measure of the LAPSUS-LS model.

[5]In these cases, staff were instructed to take a GPS reading as close to the original location as possible.

Figure 3: Maps of Two Landslide Sites Showing Exact Landslide Path, 50-Meter Buffer, and Underlying Risk



3.3 Estimating Equations

We estimate the causal impact of landslides with the following specification:

$$y_i = \beta Landslide_i + Risk_i\Omega + Site_i + X_i\Gamma + \epsilon_i \tag{1}$$

where y_i is an outcome for household i, $Landslide_i$ is an indicator for whether household i resided within 50 meters of the exact landslide path at the time of the landslide, $Risk_i$ is a vector of geological variables (elevation, slope, a landslide stability indicator, and the LAPSUS-LS risk measure of Claessens et al., 2007), $Site_i$ is a landslide-event fixed effect, X_i is a vector of possible pre-landslide controls,[6] and ϵ_i is an error term. Under our assumption

[6] Our main set of controls includes age of the male and female heads, farm size prior to the landslide, household size prior to the landslide, an indicator for whether a household member had migrated outside the village prior to the landslide, and an indicator for whether the household had family living in a big city (or, separately, in Kampala) prior to the landslide. When estimating impacts on welfare, we also include a pre-landslide welfare index based on retrospective answers. While recall bias may be a concern, this measure is not significantly correlated with residing in the landslide path.

that $Risk_i$ captures any pre-existing differences across households at the time of the landslide operating through sorting based on risk, β captures the average causal effect on y_i among households hit by the landslide, compared to households within the same area residing outside of the landslide's path, potentially holding constant pre-existing differences captured by X_i. In the results that follow, we present estimates with and without the control vector X_i. Because the LAPSUS-LS risk model is only available within certain villages in our study area, we also present results in the broader sample, dropping $Risk_i$ but maintaining the control vector X_i.

3.4 Balance

Table 1 tests whether households in the landslides' path were systematically different from other households in the same area prior to the landslide. Columns (1) and (2) show unadjusted means for several pre-landslide variables separately by unaffected and affected households. Raw mean differences are generally small: affected households were located at slightly higher elevations, had modestly largely farms prior to the landslide, and were somewhat more experienced with migration, but are otherwise very similar to unaffected households. Column (3) shows adjusted differences recovered from a regression of each pre-landslide variable on $Landslide_i$ and $Site_i$. Out of 11 pre-landslide variables, only 1 (elevation) exhibits a statistically significant difference at the 10% level, equivalent to expected differences under no selection. This indicates that selection into landslide-hit locations was likely minimal, and thus that equation 1 can be used to estimate the average causal impact of landslides. Nevertheless, we present results with and without pre-existing controls, which can help adjust for whatever differences between groups remain.

Table 1: Balance on Pre-Landslide Characteristics

	(1) Mean for Landslide=0	(2) Mean for Landslide=1	(3) Adjusted Difference
Slope	19	19	0.63
Elevation	1599	1649	22**
Ground is Stable	0.81	0.89	0.03
Critical Rainfall Value for Unstable Ground	0.07	0.05	2.6
Male Head Age (Years)	43.3	42.7	-0.9
Female Head Age (Years)	42.1	42.0	-0.16
Farm Size (Acres, Pre-Landslide)	1.9	2.4	0.49
Household Size (Pre-Landslide)	4.7	5.0	0.13
Had Migrated Prior to Landslide	0.33	0.40	0.08
Had Family in City at Time of Landslide	0.59	0.60	0.03
Had Family in Kampala at Time of Landslide	0.27	0.29	0.02

Notes: An observation is a household (based on pre-landslide structure). Columns (1) and (2) show means within unaffected and affected groups, respectively. Column (3) shows the difference recovered from a regression of each characteristic on Landslide, controlling for a landslide-event fixed effect.
*** p<0.01, ** p<0.05, * p<0.1

4 Results

This section presents the estimated impacts of landslides on immediate destruction, subsequent displacement and migration, and measures of household welfare.

4.1 Landslide Destruction

The landslides we study were highly destructive: households residing in the landslide path experience extreme rates of death and property destruction. Table 2 Column (1) shows that 45% of households in the landslides' path experienced major damage,[7] compared to 13% among households outside the path (p-val<0.01).[8] We refer to households residing in the path of the landslide as *affected households*, with the caveat that households outside the land-

[7]Among these, 83% report that their entire home was destroyed. The rest largely report damage to one or multiple walls, roofs, or destruction of the floor from flooding.

[8]There are several reasons why some of the households that we categorize as residing in the landslide's path were not damaged. Some households, especially those close to the boundary of the landslide, avoided major damage. There may also be classification error coming from GPS readings. If some unaffected households are miscategorized as affected, this should bias our impact estimates toward zero. Nevertheless, the large differences in reported damages between households categorized as residing in the landslide path and those that are not reassures us that our measure is strongly correlated with true landslide exposure.

Table 2: Destructive Impact of Landslides

	(1) House Damaged	(2) Casualty	(3) Death	(4) Land Damaged	(5) Other Damage	(6) Spending on Repairs
Panel A: Risk Control						
Landslide = 1	0.325***	0.212***	0.204***	0.163***	0.235***	296***
	(0.054)	(0.048)	(0.047)	(0.054)	(0.032)	(77)
Observations	626	626	626	626	626	626
Dep Var Mean for Landslide = 0	0.127	0.0699	0.0624	0.524	0.726	189
Panel B: All Controls						
Landslide = 1	0.315***	0.212***	0.204***	0.154***	0.220***	280***
	(0.053)	(0.048)	(0.047)	(0.054)	(0.032)	(73)
Observations	626	626	626	626	626	626
Dep Var Mean for Landslide = 0	0.127	0.0699	0.0624	0.524	0.726	189
Panel C: Full Sample						
Landslide = 1	0.377***	0.167***	0.148***	0.174***	0.218***	158***
	(0.043)	(0.036)	(0.035)	(0.043)	(0.027)	(54)
Observations	955	955	955	955	955	955
Dep Var Mean for Landslide = 0	0.186	0.0578	0.0517	0.545	0.733	233

Notes: An observation is a household (based on pre-landslide structure). Panel A regressions control for landslide risk at the pre-landslide location using a geological risk model; Panel B adds ex-ante demographic controls; Panel C expands the sample to include villages where the geologic data are missing, but retains demographic controls. All regressions include landslide-event fixed effects. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

slide path also experienced casualties and damage, albeit at a much lower rate. About 28% of affected households report casualties from the landslide (compared to 7% of unaffected households; p-val<0.01), almost all of which represents death of a household member. Both affected and unaffected households experienced damage to land, crops, livestock, or other possessions, although the rates are significantly higher among affected households. Column (7) shows impacts on uncovered repair costs incurred by households. These rise from an average of $189 among unaffected households to $485 among affected households (p-val<0.01), representing more than 9 months' worth of total household income.

4.2 Impacts on Displacement and Migration

Most households residing in the landslides' path were displaced outside their home village afterward, though a significant minority remained in the village. Table 3 Column (1) shows that even among unaffected households, 18% were displaced after the landslide; this share rises to 68% among affected households (p-val<0.01). Nearly every displaced household moved to another village in Eastern Uganda. Only seven households in our sample relocated to a city (four to Mbale, the largest town in the Eastern Region of Uganda, and two to Kampala, the capital), and one left the country. Among the 68% of affected households that were displaced, only 39%—or 24% of all affected households—remain outside their home village at the time of our survey in 2022.

In addition to displacement, the landslide increased migration. Column (3) shows that affected households sent around 0.4 additional migrants after the landslide (on a base of 1; p-val=0.04). Almost 80% of these additional migrants traveled to a city. This additional migration represents a long-run increase in the migration rate: at the time of the survey, the number of migrants from affected households is higher by 0.3 (on a base of 0.75; p-val=0.08).

4.3 Impacts on Household Welfare

Landslides substantially reduce long-run household welfare along several measures. To assess impacts on welfare, we construct five indices from our survey data following the methodology of Anderson (2008). We focus on financial health, mental health, home amenities, income, and an overall welfare index that includes all components.[9] We standardize all indices to have

[9]Our index of **financial health** includes whether the household has enough food, can pay for basic expenses, did not experience a recent financial emergency which forced asset sale, did not pull a child out of school for lack of funds, reports that they are not seriously worried about their finances, and reports that they could find 70,000 UGX in an emergency if needed. Our index of **mental health** includes whether the respondent reports that they are usually happy, usually not nervous, satisfied with their life, and optimistic about the future. Our index of **home amenities** includes indicators for whether the household has access to an improved toilet, an improved water source, an improved cooking fuel source, did not experience any crime in the past 30 days, and the number of good friends outside their household. Our index of **income** includes earnings from household businesses, earnings from individual salaries and wages, crop production value from the most recent season, savings over the past 30 days, food consumption over the past week, and

Table 3: Impact of Landslide on Displacement and Migration

	(1) Displaced Outside Village	(2) Remained Outside Village	(3) # Migrated Outside Village	(4) # Remained Outside Village	(5) # Migrated to City	(6) # Remained in City
Panel A: Risk Control						
Landslide = 1	0.500***	0.238***	0.374**	0.309*	0.293**	0.226*
	(0.051)	(0.044)	(0.184)	(0.176)	(0.149)	(0.136)
Observations	626	626	626	626	626	626
Dep Var Mean for Landslide = 0	0.181	0.0284	1.042	0.754	0.726	0.457
Panel B: All Controls						
Landslide = 1	0.489***	0.238***	0.271	0.236	0.227	0.188
	(0.050)	(0.044)	(0.166)	(0.163)	(0.138)	(0.128)
Observations	626	626	626	626	626	626
Dep Var Mean for Landslide = 0	0.181	0.0284	1.042	0.754	0.726	0.457
Panel C: Full Sample						
Landslide = 1	0.477***	0.319***	0.102	0.105	0.038	0.033
	(0.040)	(0.039)	(0.145)	(0.142)	(0.110)	(0.098)
Observations	955	955	955	955	955	955
Dep Var Mean for Landslide = 0	0.230	0.0467	1.117	0.836	0.765	0.508

Notes: An observation is a household (based on pre-landslide structure). *Displaced* refers to entire-household relocation. *# Migrated* refers to migration of household members. Panel A regressions control for landslide risk at the pre-landslide location using a geological risk model; Panel B adds ex-ante demographic controls; Panel C expands the sample to include villages where the geologic data are missing, but retains demographic controls. All regressions include landslide-event fixed effects. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

mean 0 and standard deviation 1 among unaffected households. Across all five measures, landslides have negative welfare impacts. Our overall welfare index is lower by 0.34 standard deviations (p-val=0.001) among affected households in our main specification (shown in Panel A).

the share of children who have been in school since the landslide.

Table 4: Impact of Landslide on Welfare

	(1) Welfare Index	(2) Financial Health Index	(3) Mental Health Index	(4) Home Amenity Index	(5) Income Index
Panel A: Risk Control					
Landslide = 1	-0.340***	-0.329***	-0.295***	-0.197*	-0.027
	(0.120)	(0.121)	(0.111)	(0.116)	(0.120)
Observations	626	626	626	626	626
Panel B: All Controls					
Landslide = 1	-0.427***	-0.347***	-0.325***	-0.248**	-0.115
	(0.116)	(0.120)	(0.112)	(0.113)	(0.114)
Observations	626	626	626	626	626
Panel C: Full Sample					
Landslide = 1	-0.253**	-0.308***	-0.213**	0.012	-0.119
	(0.098)	(0.101)	(0.091)	(0.111)	(0.085)
Observations	955	955	955	955	955

Notes: An observation is a household (based on pre-landslide structure). Dependent variables are standardized to have mean 0, standard deviation 1. Panel A regressions control for landslide risk at the pre-landslide location using a geological risk model; Panel B adds ex-ante demographic controls; Panel C expands the sample to include villages where the geologic data are missing, but retains demographic controls. All regressions include landslide-event fixed effects. Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.4 Potential Mechanisms

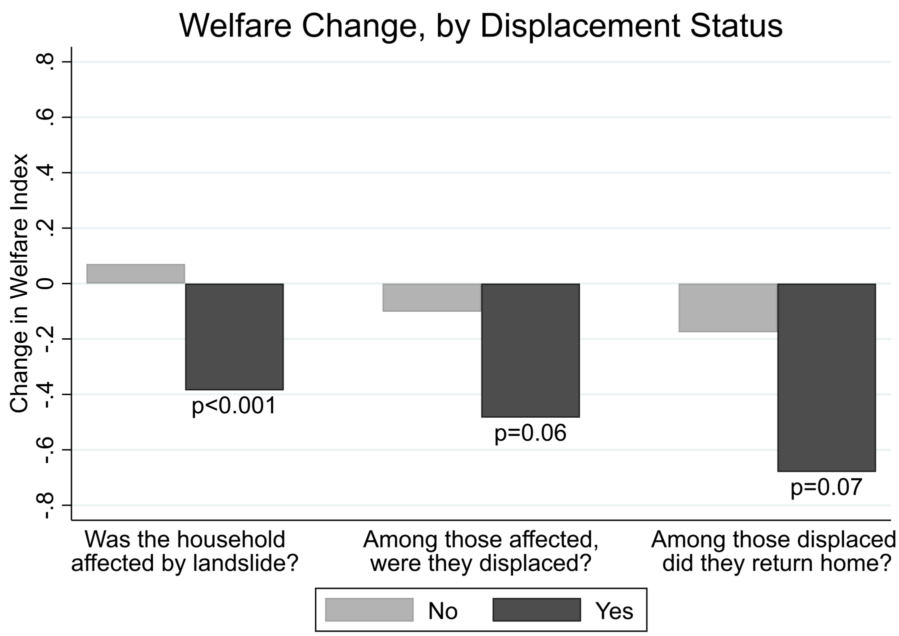
What explains the landslides' large, persistent negative impact on economic and psychological outcomes? While the damage and death toll of the landslide itself is surely a key part of the explanation, the large number of studies finding positive long-run economic impacts of natural disasters—including by disasters that exacted staggering human and economic tolls, such as the 2004 Indian Ocean tsunami—suggests that this cannot be the sole factor. One possibility is that displacement itself is permanently disruptive, by upsetting the location-specific technical and social capital that the displaced had built up. A related possibility is that the costs imposed by the landslide—both directly and by the subsequent displacement—push households into a poverty trap.

We find indirect evidence supporting both of these hypotheses. Among those affected by a landslide, displaced households experience a significantly bigger drop in welfare compared to households that remained in their home village (see Figure 4). Among those displaced, the drop in welfare is pronounced among households that moved again to return to their home village (the majority of those who did not return remained in the destination to which they were displaced).[10] The greater welfare drop among returnees is somewhat surprising, and is difficult to reconcile with the loss of origin-specific factors, such as social networks, as being the primary driver of welfare change. Indeed, only about one-third of returnees give a reason for returning that reflects a voluntary choice, such as to reclaim land, because they did not like life in the destination, or because others were also moving back. The rest move back because they can no longer afford living in the destination, or only had temporary arrangements.

We further explore potential mechanisms behind the landslides' impact on migration and welfare by interacting the *Landslide* indicator with three proxies for a household's risk coping ability: an indicator for having family living in Kampala (the capital) at the time of the landslide; an indicator for whether the household lost less than half its land, the median value among affected households; and an indicator for whether at least 50% of the damages incurred during the landslide were covered by external aid. Having family in big cities such as Kampala can help affected households cope by increasing their remittances. Land loss makes remaining in the village much more difficult: among affected households, high land loss strongly predicts displacement. Aid can help households cope by ensuring they have enough money to cover essential expenses, and thus give them greater choice in where and for how long they are displaced. Aid receipts in this context were quite small: the median

[10]To partly address the concern that pre-existing welfare differences may have driven displacement among those affected, or driven return decisions conditional on displacement, we compute the change in welfare from before the landslide to the present by taking our contemporaneous welfare index and subtracting a pre-landslide retrospective measure. Although this could introduce concerns about recall bias, pre-existing welfare is not significantly different between affected and unaffected households. Results are consistent, though noisier, when using contemporaneous welfare as the outcome.

Figure 4: Displaced Households Experienced Greater Welfare Declines



Notes: Coefficients recovered from a differences-in-differences regression interacting $Landslide_i$ with an indicator for displacement outside the village and an indicator for returning to the village. Welfare index is an Anderson (2008) index of survey questions on financial health, mental health, home amenities, and income (see Section 4.3 for a list of components). Change in welfare is the difference between the current and the retrospective, pre-landslide index value.

damaged household received about \$5 in aid, and even households in the landslide's path received only about \$33, or 10% of the median cost of repairs.

Table 5 presents results. Having family in Kampala reduces urban migration following the landslide (p=0.02), consistent with new migration acting as a substitute risk coping mechanism. Increased aid receipts and low land loss are associated with partly mitigated negative welfare impacts of the landslide, though differences are imprecisely measured (p-values are 0.2 and 0.36 respectively). Taken together, these results suggest that forced relocation itself can help explain the negative long-run impact of landslides. Factors that allow households to cope with the damage caused by landslides—including urban networks and aid receipts—can also have long-run impacts on welfare.

Table 5: Potential Mechanisms Behind Urban Migration and Welfare Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	# Migrants Sent to City			Welfare Index		
Landslide * Family in Kampala	-0.581**			-0.138		
	(0.272)			(0.264)		
Landslide * Retained Land		0.299			0.216	
		(0.289)			(0.233)	
Landslide * Received Aid			-0.324			0.341
			(0.286)			(0.264)
Family in Kampala	0.193			0.173		
	(0.118)			(0.106)		
Retained Land		-0.022			0.007	
		(0.101)			(0.088)	
Received Aid			0.072			-0.144
			(0.116)			(0.101)
Landslide	0.460**	0.131	0.265	-0.304**	-0.454***	-0.503***
	(0.193)	(0.185)	(0.180)	(0.138)	(0.160)	(0.136)
Dep Var Mean in Omitted Group	0.953	0.735	0.868	0.003	-0.025	-0.180
Observations	626	626	626	626	626	626

Notes: An observation is a household (based on pre-landslide structure). Each column shows a difference-in-difference regression interacting the landslide dummy with an indicator for one of three proxies for risk coping ability. *Family in Kampala* refers to the time preceding the landslide. *Retained Land* is an indicator for whether the household lost less than half of its land in the landslide. *Received Aid* is an indicator for whether at least 50% of landslide damages were covered by external aid. All regressions include landslide-event fixed effects and control for geologic risk. Regressions in Columns (3) and (6) additionally control for total damage caused by the landslide. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

5 Discussion

Natural disasters displace millions of people a year, but are difficult to study because displacement makes data collection very difficult, and because people tend to sort out of high-risk areas. We overcome these challenges by combining information on exact landslide paths—which produce quasi-random variation in destruction within affected areas—with complete administrative lists of the set of households residing in the affected villages at the time of the landslide event. This allows us to estimate the average causal impact of landslides on the affected population. Extensive tracking of households no longer living in the village made this possible in a setting with very high rates of displacement. This study thus offers a rare look at the household-level impact of a natural disaster that displaced a high number of households.

We find that households affected by landslides are much more likely to be displaced to a different rural location, to send migrants to urban locations, and appear significantly worse along several measures of economic and psychological health. The negative impacts on welfare are pronounced among households that were displaced by the landslide, and even more so for those that relocated again back to their origin village. There is suggestive evidence that aid receipts can mitigate long-run impacts by helping households cope with landslide shocks. This may explain why other studies of natural disasters—which study contexts in which displacement is rare or households were insured against losses—often find small or even positive long-run economic impacts.

References

Abramitzky, Ran, Travis Baseler, and Isabelle Sin, "Persecution and Migrant Self-Selection: Evidence from the Collapse of the Communist Bloc," Working Paper 30204, National Bureau of Economic Research July 2022.

Akoyi, Kevin Teopista and Miet Maertens, "Walk the talk: private sustainability standards in the Ugandan coffee sector," *The Journal of Development Studies*, 2018, *54* (10), 1792–1818.

Aksoy, Cevat Giray and Panu Poutvaara, "Refugees' and irregular migrants' self-selection into Europe," *Journal of Development Economics*, 2021, *152*, 102681.

Anderson, Michael L., "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American Statistical Association*, 2008, *103* (484), 1481–1495.

Becker, Sascha O. and Andreas Ferrara, "Consequences of forced migration: A survey of recent findings," *Labour Economics*, 2019, *59*, 1–16. Special Issue on "European Association of Labour Economists, 30th annual conference, Lyon, France, 13-15 September 2018.

Cattaneo, Cristina and Giovanni Peri, "The migration response to increasing temperatures," *Journal of Development Economics*, 2016, *122*, 127–146.

Chin, Aimee and Kalena E. Cortes, *The refugee/Asylum seeker*, 1 ed., Vol. 1, Elsevier Inc., 2015.

Chiovelli, Giorgio, Stelios Michalopoulos, Elias Papaioannou, and Sandra Sequeira, "Forced Displacement and Human Capital: Evidence from Separated Siblings," Working Paper 29589, National Bureau of Economic Research December 2021.

Claessens, L, Anke Knapen, MG Kitutu, Jean Poesen, and Jozef A Deckers, "Modelling landslide hazard, soil redistribution and sediment yield of landslides on the Ugandan footslopes of Mount Elgon," *Geomorphology*, 2007, *90* (1-2), 23–35.

Claessens, Lieven, Mary G Kitutu, Jean Poesen, and Jozef A Deckers, "Landslide hazard assessment on the ugandan footslopes of Mount Elgon: the worst is yet to come," in "Landslide Science and Practice," Springer, 2013, pp. 527–531.

Cortes, Kalena E, "Are Refugees Different From Economic Immigrants? Some Empirical Evidence On The Heterogeneity Of Immigrant Groups In The United States," *Review of Economics and Statistics*, 2004, *86* (2), 465–480.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt, "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns," *American Economic Journal: Applied Economics*, April 2018, *10* (2), 202–33.

Gignoux, Jérémie and Marta Menéndez, "Benefit in the wake of disaster: Long-run effects of earthquakes on welfare in rural Indonesia," *Journal of Development Economics*, 2016, *118*, 26–44.

Gray, Clark, Elizabeth Frankenberg, Thomas Gillespie, Cecep Sumantri, and Duncan Thomas, "Studying displacement after a disaster using large-scale survey methods: Sumatra after the 2004 tsunami," *Annals of the Association of American Geographers*, 2014, *104* (3), 594–612.

Gröger, André and Yanos Zylberberg, "Internal labor migration as a shock coping strategy: Evidence from a typhoon," *American Economic Journal: Applied Economics*, 2016, *8* (2), 123–53.

Heger, Martin Philipp and Eric Neumayer, "The impact of the Indian Ocean tsunami on Aceh's long-term economic growth," *Journal of Development Economics*, 2019, *141*, 102365.

IDMC, "Disaster Displacement: A global review, 2008–2018.," *Internal Displacement Monitoring Centre*, 2019.

Independent, The, "Revisiting Nametsi 10 years after landslides," *The Independent, Uganda*, 2020.

Knapen, Anke, M Goretti Kitutu, Jean Poesen, W Breugelmans, J Deckers, and A Muwanga, "Landslides in a densely populated county at the footslopes of Mount Elgon (Uganda): characteristics and causal factors," *Geomorphology*, 2006, *73* (1-2), 149–165.

Monitor, "Landslides kill 1,000 in Bugisu over the past decade.," *Monitor*, 2019.

Nakamura, Emi, Jósef Sigurdsson, and Jón Steinsson, "The Gift of Moving: Intergenerational Consequences of a Mobility Shock," *The Review of Economic Studies*, 09 2021, *89* (3), 1557–1592.

Noy, Ilan, "The macroeconomic consequences of disasters," *Journal of Development economics*, 2009, *88* (2), 221–231.

OCHA, "Uganda: Floods and Landslides.," *United Nations Office for the Coordination of Humanitarian Affairs*, 2019.

Sacerdote, Bruce, "When the Saints Go Marching Out: Long-Term Outcomes for Student Evacuees from Hurricanes Katrina and Rita," *American Economic Journal: Applied Economics*, January 2012, *4* (1), 109–35.

World Bank Group, "Climate Risk Profile: Uganda," 2020.

Appendix A. Additional Tables and Figures

Table A1: Robustness to Definition of Households Affected by Landslide

	(1) Casualty	(2) Spending on Repairs	(3) Displaced Outside Village	(4) Remained Outside Village	(5) Welfare Index
Panel A: Self-Reported Home Damage					
Home Damage = 1	0.226***	588***	0.390***	0.151***	-0.347***
	(0.044)	(86)	(0.049)	(0.037)	(0.104)
Observations	626	626	626	626	626
Dep Var Mean for Home Damage = 0	0.0645	129	0.188	0.0371	0.0145
Panel B: Within Exact Landslide Site					
Within Site = 1	0.257***	233**	0.516***	0.332***	-0.259
	(0.077)	(117)	(0.066)	(0.072)	(0.168)
Observations	626	626	626	626	626
Dep Var Mean for Within Site = 0	0.0832	214	0.220	0.0399	-0.0306

Notes: An observation is a household (based on pre-landslide structure). *Home Damage* is an indicator for whether the houseohld reported damage to their home from the landslide. *Within Site* is an indicator for whether the household resided in the exact landslide site (that is, without using a 50-meter buffer) at the time of the landslide. All regressions include landslide-event fixed effects and control for landslide risk at the pre-landslide location using a geological risk model. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

www.theigc.org