Disastrous Displacement:
The Long-Run Impacts of Landslides*

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Abstract

Natural disasters displace millions of people a year. Past studies of disasters have shown that displacement can improve economic outcomes, but focus on events that precipitated a substantial government or international aid response. Little is known, however, about disaster impacts when institutional capacity is low. This paper estimates the long-run impacts of landslides in Uganda, where most affected households received little external assistance. The analysis combines administrative and survey data from nearly the full population of affected and nearby households with exact landslide paths and a geological model of landslide risk to identify impacts relative to nearby households facing similar risk. Landslides substantially increase long-term displacement and migration, and affected households have significantly worse economic and mental health outcomes years afterward. Displacement worsens long-run outcomes, especially when not administered by the government. These findings suggest that the positive impacts of displacement require a favorable financial and institutional environment unlikely to be found in many countries.

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1 Introduction

Between 2008 and 2018, around 265 million people were displaced by natural disasters such as floods, storms, earthquakes, tsunamis, and landslides, and the frequency and severity of these disasters are expected to increase (IDMC, 2019). There is thus a clear need to understand the economic impacts of natural disasters and subsequent displacement on affected individuals, as well as the factors that mitigate harmful effects. However, the nature of displacement makes estimating these impacts difficult, especially in developing countries where the vast majority of at-risk individuals reside. 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. Displacement itself also complicates data collection—especially on long-run outcomes—as the affected population becomes dispersed. These challenges have led to a paucity of such estimates in the economics literature, especially in developing countries. The few studies of natural disaster in developing countries focus on events that attracted massive international attention and aid—such as the 2004 Indian Ocean tsunami—but most natural disasters receive little attention or aid, and disaster impacts in these settings are largely unknown (Eisensee and Strömberg, 2007, Heger and Neumayer, 2019).[1]

This paper studies the long-run economic impacts of landslides in Uganda, where 300,000 people have been affected, and 65,000 displaced, over the past decade alone (OCHA, 2019). Heavy precipitation events were an important factor in these disasters, and are expected to become more frequent (World Bank Group, 2020). We identified six major landslide events in eastern Uganda since 2010, and gathered administrative lists of the households residing in the affected areas at the time of each landslide. We surveyed those households in 2022 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 different than the impact on the set of households that remain, especially in settings with high rates of displacement. To identify causal impacts, we use exact information on the path of each landslide and households' pre-landslide locations. Applying a risk model developed in the geomorphology literature specifically for our study region (Claessens et al., 2007), we

[1] Aid following the 2004 Indian Ocean tsunami totaled $1,250 per victim (Péchayre, 2011), far exceeding direct monetary damages in what Heger and Neumayer (2019) call "the single largest aid and reconstruction effort of any developing world region ever afflicted by a natural disaster." The average large disaster prompts far less aid, totaling about 10% of damages on average (Heger and Neumayer, 2019). This average is close to aid receipts in our setting, which amounted to about 8% of monetary damages.

show that around a landslide site, many households that did not experience a landslide nevertheless faced similar levels of risk compared to those that did.[2] Before the disaster, directly affected households did not differ from their neighbors on a large set of observable characteristics, consistent with limited sorting into the landslide paths within an affected site. We estimate long-run impacts by comparing landslide-affected households to their neighbors, controlling for *ex-ante* landslide risk as measured by the geomorphological model.[3]

The landslides were highly destructive, causing casualties in 28% of households residing in their paths—which we refer to as *affected households*—and average damages worth over two years of median household income. The landslides also created substantial displacement: affected households were 50 percentage points (pp.) more likely to be displaced outside their home villages, with almost all moving to rural locations. However, external assistance was low: the average affected household received only $34 in aid—about 8% of damages—and only 24% of displacements were administered by the government. By the time of our surveys—between 3 and 12 years after the landslide events—about 60% of displaced households had returned to their home villages. The landslides also increased rural-to-urban migration of individuals within the household, which persists in the long run. Years after the landslides, affected households appear substantially worse off compared to those that were outside a landslide path: they are less likely to be economically active, they exhibit worse economic and mental health outcomes, and they live in lower-quality housing. These negative welfare impacts appear much worse for households that were displaced outside their home villages, especially when the government did not administer the resettlement process. Casualties among household members are also strongly predictive of negative long-run impacts. The negative welfare impacts appear partly mitigated for households that sent more migrants to urban areas after the landslide, suggesting that urban migration can help affected households cope with the impacts of disaster.

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 with little

[2]While the overall risk of landslides in the area is known, the extent and path of each slide introduces plausibly exogenous variation in landslide damage. This is supported by a literature showing the difficulty of predicting landslide occurrence, and especially landslide extent, from geological variables (Broeckx et al., 2019, Roy et al., 2022).

[3]Our identification strategy does not capture broader regional impacts, such as those at the village level. In Section 4.4, we argue that the presence of regional effects is likely to cause us to understate the negative impacts of landslides on directly affected households. We use data on households far from landslides to show that regional effects appear small compared to differences between affected and nearby households.

assistance. This finding is in stark contrast to many estimates from developed countries, which often find positive long-run impacts of displacement on income and human capital, possibly by disrupting locational ties that have adverse economic consequences or increasing human capital investment (Sacerdote, 2012, Deryugina et al., 2018, Becker et al., 2020, Nakamura et al., 2021). A number of studies in low-income settings have also found positive long-run economic impacts of natural disasters (Gignoux and Menéndez, 2016, Heger and Neumayer, 2019), potentially driven by subsequent aid receipts. Our results are consistent, however, with a more qualitative or descriptive medical literature that documents negative mental health outcomes associated with natural disaster and displacement (Norris et al., 2002, Porter and Haslam, 2005, Makwanam, 2019), including in eastern Uganda (Kabunga et al., 2022). This contrast suggests that the positive impacts of disaster observed in other settings may reflect the returns to aid, as opposed to the impacts of disaster or displacement *per se*. Importantly, the contextual differences between our study and the extant literature mirror the variation within our setting: among households affected by the landslides, those that experienced unassisted displacement experience much worse long-run outcomes.

Based on the divergence between our results and others in the literature—and supported by the apparent role that external assistance played in our setting—we argue that the positive long-run economic impacts found in much of the literature on natural disasters are likely driven by the same factors that facilitate data collection and causal estimation: well-developed institutions which can provide insurance or disburse aid. Our study presents a rare opportunity to bring the tools of causal identification to a context with insufficient institutional capacity to cope with disasters. As the majority of disaster-driven displacement occurs in sub-Saharan Africa and South and Southeast Asia (IDMC, 2019, Internal Displacement Monitoring Centre, 2022), where government capacity to respond to disasters is often limited, these findings have significant implications for the global population of at-risk households.

This paper contributes most directly 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 town in Iceland. The authors find that displaced households were better educated and earned more, with results driven by younger individuals for whom high moving costs may have precluded 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 were higher by the third year following displacement. These two papers attribute the positive impacts of displacement to locational advantages in the destination compared to the origin.

Positive long-run impacts have also been documented in the literature studying natural disasters in developing economies.[4] Gignoux and Menéndez (2016) and Heger and Neumayer (2019) study the long-run effects of earthquakes and a 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 responses to a typhoon in Vietnam, and find that households cope with the negative shock to income through increased remittances from existing migrants and by sending new migrants to urban areas, but do not measure long-run effects.[5] 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 from a developing country to study the impact of a natural disaster involving substantial household displacement, which we show appears to mediate welfare impacts. We also add to this literature by documenting persistent negative impacts of disaster on households' mental health, which many existing natural-disaster studies are unable to evaluate. Finally, we introduce to this literature a novel measure of *ex-ante* landslide risk based on geological features such as terrain slope and soil characteristics, assisted by a model from the geomorphology literature (Claessens et al., 2007).

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 displacement during the Mozambican civil war on human, social, and civic capital by comparing displaced to non-displaced siblings in census data. The authors find that displacement increases educational investment. While the greatest effects were observed in rural-to-urban movers, even rural-rural movers exhibited greater educational gains than stayers, implying that place-based effects do not

[4] At the macroeconomic level, Noy (2009) finds that less developed countries are less able to withstand shocks from natural disasters.

[5] For evidence that remittances help households cope with negative weather shocks, including natural disasters, see Yang and Choi (2007), Yang (2008), Blumenstock et al. (2016) and Mahajan and Yang (2020).

entirely drive displacement impacts. Sarvimäki et al. (2022) show that displacement of Finnish communities after WWII increased long-run income, possibly due to disrupted preferences for remaining in a home location that did not maximize individuals' incomes. In our setting, we find large negative welfare impacts among displaced households who moved to similar rural locations, or who later returned to their home village, indicating negative displacement effects.[6] Cortes (2004), Gray et al. (2014), Chin and Cortes (2015), Dustmann et al. (2017), 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. [7] 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 recurring violence or instability, implying that displacement effects relative to a conflict-free counterfactual are difficult to estimate.[8] Our study adds to this literature by showing that natural disaster-driven displacement can have significant negative long-run welfare consequences in a setting characterized by high casualty rates and rural-rural moves.

Finally, our paper contributes to the study of rural-urban income gaps in developing countries, and the role of internal migration in allowing households to exploit these gaps. A large literature finds barriers that restrict workers from moving to take advantage of income gaps, including inadequate information about destination opportunities (Baseler, 2023), financial constraints (Bryan et al., 2014, Cai, 2020), costs of migrating (Lagakos et al., 2018, Imbert and Papp, 2020, Morten and Oliveira, 2023), food insecurity in the destination (Baseler et al., 2023), and land market frictions (De Janvry et al., 2015).[9] While worker sorting also plays a role in sustaining income gaps (Lagakos and Waugh, 2013, Young, 2013, Hamory et al., 2020), several studies find that the return to marginal rural-urban migration in low-income countries is large (Beegle et al., 2011, Bryan et al., 2014, Baseler, 2023). These large, uncaptured returns are thought to explain the positive effects of displacement observed in some contexts through place-based effects on earnings (Deryugina et al., 2018, Chiovelli et al., 2021, Nakamura et al., 2021). Our results are consistent with posi-

[6]The contrast between our results and those in Chiovelli et al. (2021) may be due to a greater difference in casualty rates between the displaced and the non-displaced, a point we return to in Section 4.1.

[7]Cattaneo and Peri (2016) study the impact of rising temperatures on migration, but also do not estimate impacts on the displaced. See Becker and Ferrara (2019) for a review of the forced migration literature.

[8]We find that indirect impacts of landslides on nearby households not directly hit by the landslides were likely small relative to direct impacts: see the discussion in Section 4.4.

[9]See Lucas (1997) and Lagakos (2020) for reviews of this literature.

tive returns to disaster-induced urban migration, but we find that rural-rural displacement worsens welfare impacts. This literature has also documented that migration can help households cope with disasters, by offering earnings opportunities for new migrants (Mahajan and Yang, 2020) or through increased remittances from existing migrants (Yang and Choi, 2007, Yang, 2008). We confirm in our setting that landslides increase rural-urban migration, which helps households cope with the disaster.

This paper proceeds as follows. Section 2 describes our setting and study design, including our sampling frame, identification strategy, and estimating equations. Section 3 presents results. Section 4 discusses potential mechanisms driving those results—focusing on casualties and damage from the landslides, displacement and return, government resettlement assistance, and rural-urban migration—and rules out potential alternative explanations. Section 5 concludes.

2 Study Design

This section describes the setting of our study, our data collection methodology, and our identification strategy to estimate the causal impacts of landslides.

2.1 Context and Geological Data

Our study area is the Mt. Elgon region of eastern Uganda, where most of the landslide-related deaths and displacement in Uganda have occurred. Between 2010 and 2020, landslides resulted in at least 1,000 deaths in the region, and in tens of thousands of displacements.[10] The main hot spot for these disasters is Bududa district. The volcanic soils and steep slopes of Bududa contribute to landslide risk, as do the increasing population density and intensity of crop cultivation (Knapen et al., 2006, Claessens et al., 2007). The primary economic activity is farming, especially of maize and bananas, and of coffee as a cash crop (Akoyi and Maertens, 2018).

Despite attempts by the Ugandan government to relocate victims and the at-risk population, the number of households facing serious landslide risk has grown over time (Independent, 2020). This risk is closely related to climate change, in particular more frequent heavy rainfall events, which

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

destabilize susceptible slopes. The number of landslides and floods has increased over the last 30 years, and is expected to increase further (World Bank Group, 2020).

Bududa has frequently been the site of geological landslide risk assessments, for example in Claessens et al. (2007, 2013) and Broeckx et al. (2019). 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, direction, 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. As described in Section 2.3, we use this output—together with information on each site's topography—to control for households' pre-existing exposure to landslide risk, and in Section 2.5 we show that directly affected households did not differ from their neighbors before the disaster along a large set of observable characteristics.

2.2 Site Identification and Household Data Collection

The sample for our study includes the largest landslide sites around Bududa in the last 10 years. For each site, we collected a list of households residing in nearby villages *at the time of the landslide* from past population registers maintained by local officials. This gives us information on the full affected population regardless of whether they moved away. These lists form our study sample. We also collected data from two other landslide sites outside Bududa district. LAPSUS-LS data are not available in these other districts, so our main analysis relies on the four Bududa sites.[11]

The population registers produced a list of 975 households, of which 652 were located in Bududa. We supplemented this list using snowball sampling by inquiring about neighboring households not on the household register during fieldwork. Only 26 new households were identified through this process, increasing our confidence that the registers were largely complete.

Of the 675 households we identified as residing in our study villages in Bududa prior to the landslide in their area, we successfully surveyed 630, or 93%. We successfully collected GPS readings at the pre-landslide location for all but five of these households, producing a final primary

[11] Results including the two additional sites are very similar, as shown in Appendix Table A9.

sample of 625 households. In the broader sample which includes Manafwa and Sironko districts, we successfully surveyed 913 out of 1,001 households, or 91%. Inclusion in our sample is uncorrelated with household size or age of the household head, and is similar across the four landslide sites, as shown in Appendix Table A1. Our survey rate is higher for households that were still residing in their original village. Out of the 675 households, 46 (6.8%) were listed as currently living in a different village. Among these 46, we successfully surveyed 36 (78%).[12] Our surveys collected current and pre-landslide information for each individual that had been living in that household prior to the landslide, regardless of their current location. Additional details on sampling and data collection can be found in Appendix B.

Figure 1 displays our six sites on a map of the surrounding region. We surveyed households from four sites within Bududa district, where we can estimate landslide risk from LAPSUS-LS data. We also identified two sites in the neighboring Manafwa and Sironko districts.[13]

2.3 Identifying Variation

To identify which households were hit by landslides, we used satellite images to trace exact landslide paths. We add a 50-meter buffer to these paths to account for rubble or destabilized ground near the path's boundary that may not show up on satellite images.[14] We designate households that had been residing within these buffered regions at the time of the landslide as *affected households*, with the caveat that households outside a landslide path also experienced casualties and damage, albeit at a much lower rate. We show that our main results are similar when excluding the 50-meter buffer, or relying on self-reported damages, in Tables A4 and A5.

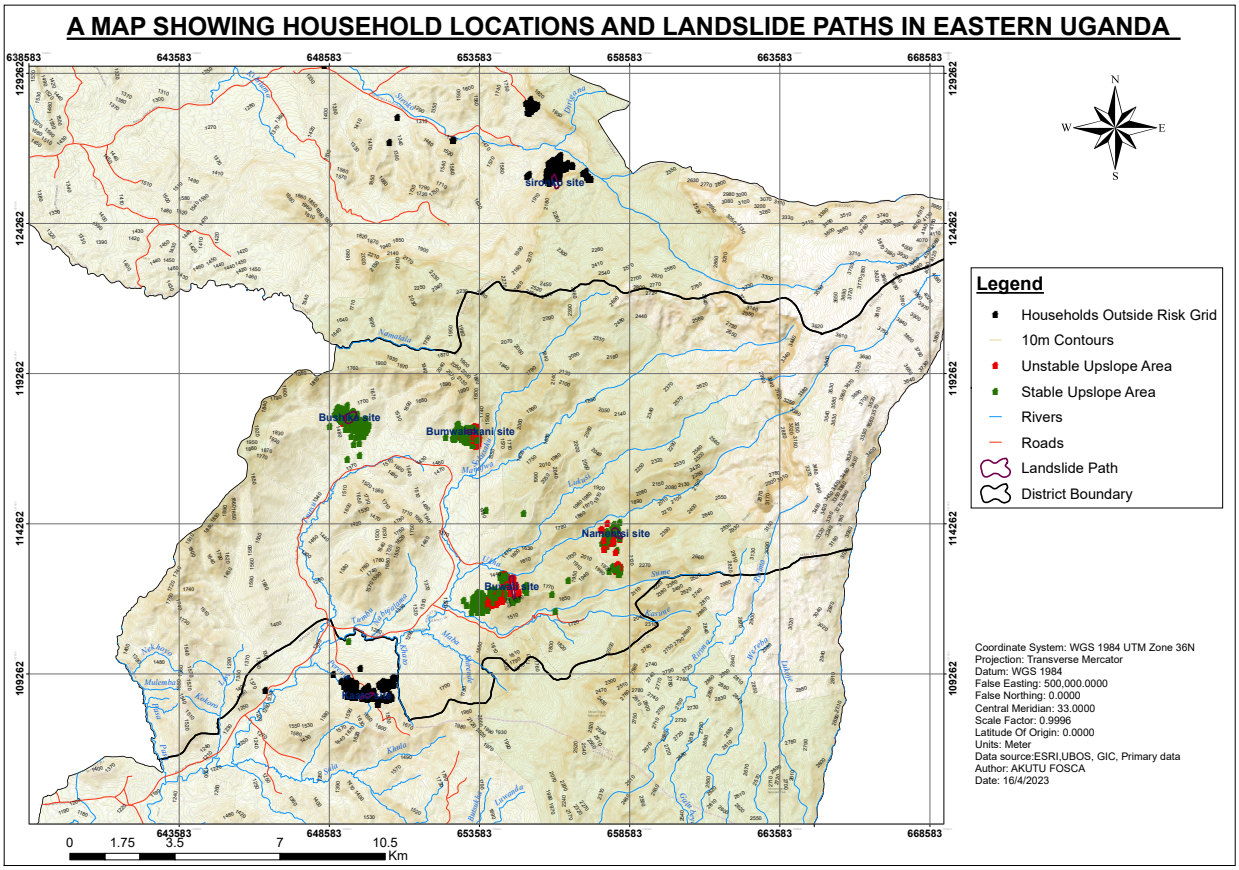
To control for possible *ex-ante* sorting based on landslide risk, we combine information from the LAPSUS-LS model with information on each site's topography to compute measures of exposure to landslide risk at each household's pre-landslide location. Specifically, we compute the

[12] We discuss the possibility that the lower survey rate among households listed as currently displaced is driving our estimates in Section 4.4. Re-weighting our estimates to account for non-response changes them very little, as shown in Appendix Table A10.

[13] The Bududa sites include the large Nametsi landslide in 2010, an equally destructive event in Bumwalukani parish in 2012, and two more recent events: the 2019 landslides in Bushika and Buwali sub-counties, which together killed close to 100 residents and displaced more than 1,000. The two sites outside Bududa are a 2018 landslide in the Kaato sub-county of Manafwa and a 2017 landslide in the Bufupa parish of Sironko.

[14] We choose 50 meters as a buffer because of a clear discontinuity in how likely households are to report destruction of their home around that point, as shown in Appendix Figure A1.

Figure 1: Overview of Landslide Sites in Our Study Sample



Notes: Each house icon is the pre-landslide location of a household in our sample. Green indicates that more than 75% of that household's upslope area is classified as stable; red indicates that 25% or more of the upslope area is classified as unstable. Exact landslide paths shown in purple polygons.

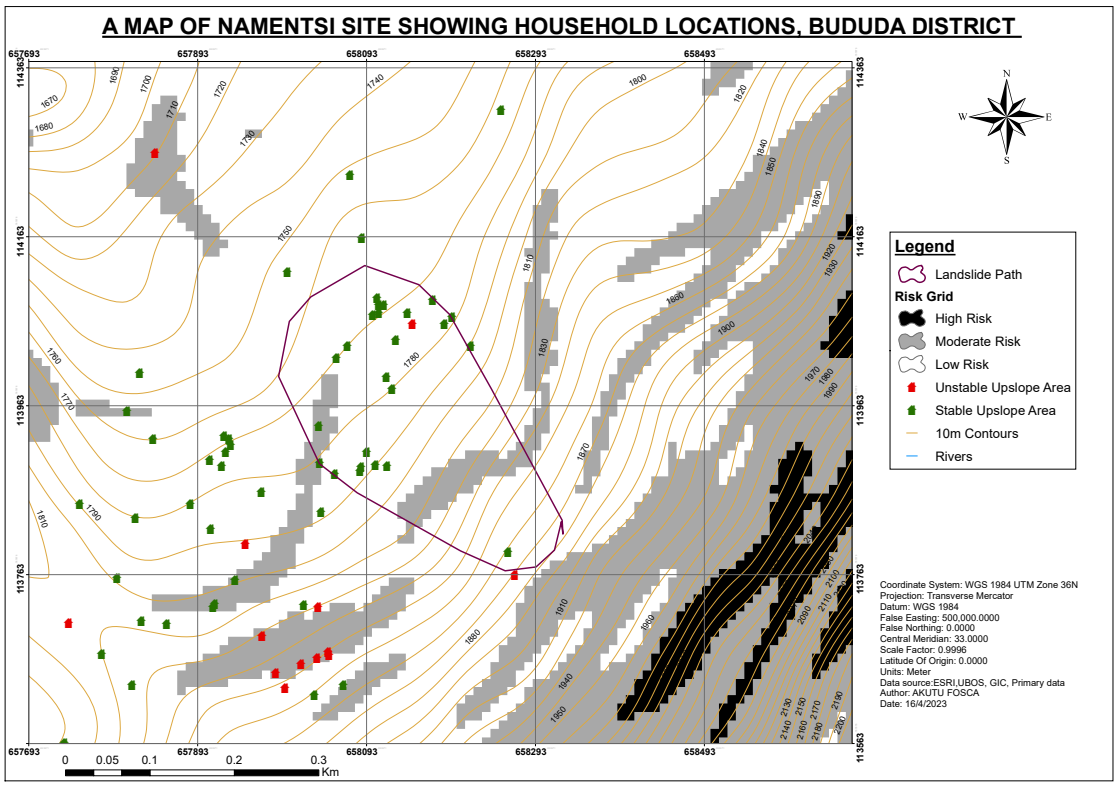
share of the upslope area classified as unconditionally unstable, the share classified as conditionally unstable, and the distance to the nearest unconditionally unstable point.

Figure 2 displays our identification strategy visually for the Namentsi landslide site in Bududa district.[15] The map shows the Claessens et al. (2007) measure of soil instability at each surface-grid point, with darker shading indicating a higher risk of instability. Households in our sample are colored green or red according to their exposure to unstable upslope terrain: households in red were located where 25% or more of the total upslope area is classified as unstable. The exact landslide path is shown in purple. The map provides a preliminary indication that predicting landslide paths is difficult: there is significant variation in exposure to unstable upslope terrain both within and outside the *ex-post* landslide path.[16] In Section 2.5, we show that the LAPSUS-LS variables,

[15]Maps of our other study sites are presented in Appendix Figure B1.

[16]The unpredictability of landslide extent is also discussed in Broeckx et al. (2019), which uses an updated model

Figure 2: Map of One Landslide Site Showing Grid-Level Soil Instability, Household-Level Risk, and Exact Landslide Path



Notes: Land surface is shaded to indicate soil instability at that grid point: black indicates high risk (unconditional instability), gray indicates moderate risk (critical rainfall value of up to 0.39 meters per day), and white indicates low risk (critical rainfall higher than 0.39 meters per day). Each house icon is the pre-landslide location of a household in our sample. Green indicates that more than 75% of that household's upslope area is classified as stable; red indicates that 25% or more of the upslope area is classified as unstable. Exact landslide path shown in purple polygon. We apply a 50-meter buffer (not shown) when classifying affected households to account for GPS readings taken near the boundary, and for rubble or destabilized ground not captured in the exact path.

our measures of households' landslide risk, and other pre-landslide demographic variables exhibit few significant differences between households originally located in a landslide path relative to their neighbors. This is indicative of limited sorting of households across affected and unaffected locations within sites.

to study Bududa district; while they find that overall landslide susceptibility of an area can be assessed, the size of a slide and thus its width and length are difficult to predict from observed characteristics. The changing nature of landslide risk as a consequence of climate change can make previously safe areas prone to instability (World Bank Group, 2020). This is also reflected in the government's plans to relocate all households in landslide-prone areas (Kabunga et al., 2020), rather than targeting certain households within these areas.

2.4 Estimating Equations

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

$$y_i = \beta Landslide_i + Risk_i\Omega + Site_i + \varepsilon_i \quad (1)$$

where y_i is an outcome (which may be measured at the household or individual level); $Landslide_i$ is an indicator for whether the household resided within 50 meters of the exact landslide path at the time of the landslide; $Risk_i$ is a vector of geological variables defined at households' pre-landslide locations (elevation, slope, indicators for ground stability classifications defined in Claessens et al., 2007, the share of the upslope catchment area classified as unconditionally unstable and as conditionally unstable, the distance to the nearest unstable point, and the square of that distance);[17] $Site_i$ is a landslide-event fixed effect; and ε_i is an error term.[18] Under our assumption that $Risk_i$ captures any pre-existing differences at the time of the landslide across households within a landslide site operating through sorting based on risk, β captures the average causal effect of landslides on y_i among households hit by the landslide, compared to households within the same area residing outside of a landslide path, potentially holding constant pre-existing observable demographic differences. If households outside a landslide path are also negatively affected, for example through damages from the associated heavy rains or disruptions in village infrastructure or public services, this will lead us to understate any negative impacts of landslides on households within a landslide path, a point we return to in Section 4.4.

By nature, the destruction caused by landslides is spatially clustered and so may give rise to spatial correlation in regression residuals. Appendix Table C1 presents Moran tests for spatial correlation in residuals for our main outcomes. These Moran tests suggest the presence of only modest spatial correlation: out of 14 outcomes, we reject the null hypothesis of independent and

[17] Consistent with our finding of limited sorting around the *ex-post* landslide path, omitting this risk measure produces very similar estimates (see Appendix Table A7).

[18] When estimating impacts outside our main sample, where LAPSUS-LS data are not always available, we include pre-landslide demographic controls as a substitute for the geological controls in $Risk_i$. Estimates in Bududa are robust to controlling for 5-year bins of the respondent's age, farm size prior to the landslide, household size and number of adult-equivalents 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, as shown in Appendix Table A6. When using these controls, we replace missing values with the mean value among non-missing responses.

identically distributed error terms at the 10% level for two. Appendix Tables C2 and C3 present standard errors adjusted for spatial correlation using the method of Conley (1999) and Müller and Watson (2022) respectively. These adjusted standard errors are very similar to their unadjusted versions.

2.5 Balance on Pre-Landslide Characteristics

Consistent with qualitative evidence that landslide paths are difficult to predict within an area (see footnote 16), households located in a landslide path exhibit few significant pre-existing differences compared to other households in the same area, as shown in Table 1. Columns 1 and 2 show unconditional means for several pre-landslide variables separately by unaffected and affected households, and Column 3 shows the average difference for each variable estimated using (1).[19] Average differences are generally small: out of 28 pre-landslide variables spanning geography, demographic information, and retrospective income and savings, only 3 exhibit significant differences at the 10% level. Affected households were located at slightly higher elevations and slightly *farther* from the nearest unstable point, and had modestly larger farms prior to the landslide, but are otherwise very similar to unaffected households.[20] We thus proceed to estimate the casual impacts of landslides using (1).

3 Short- and Long-Run Impacts of Landslides

This section presents our estimated impacts of landslides on immediate destruction, subsequent displacement and migration, and long-run economic and mental health outcomes. Throughout this paper we distinguish between displacement—the relocation of an entire household due to landslide—and migration—the departure of one or more individuals from a household to seek work outside the village.

[19] We include the vector *Risk* to control for geological risk only in Panels B and C.

[20] We present results estimated on the set of households with common support of these three imbalanced variables in Appendix Table A8. The results are very similar to our main estimates.

Table 1: Balance on Pre-Landslide Characteristics

	(1) Mean for Unaffected Households	(2) Mean for Affected Households	(3) Conditional Difference	(4) p-Value	(5) N
Panel A: Geography at Pre-Landslide Location					
Terrain Slope	19	19	0.6	0.38	625
Elevation (Kilometers)	1.60	1.65	0.02**	0.04	625
Ground is Stable	0.81	0.89	0.03	0.49	625
Critical Rainfall Value for Unstable Ground	0.07	0.05	-0.02	0.28	111
Size of Upslope Area (meters squared)	1832	1495	-380	0.24	625
Size of Unstable Upslope Area (meters squared)	576	415	-109	0.58	625
Stable Upslope Area (% of total)	0.77	0.84	0.03	0.44	625
Unconditionally Unstable Upslope Area (% of total)	0.00	0.01	0.01	0.14	625
Conditionally Unstable Upslope Area (% of total)	0.23	0.15	-0.04	0.25	625
Distance to Nearest Unstable Point (meters)	704	752	-105***	0.00	625
Panel B: Demographic Characteristics					
Respondent Age (Years)	44	43	-0.77	0.71	613
Average Household Age (Pre-Landslide)	29	28	-0.85	0.59	604
Household Size (Pre-Landslide)	4.7	5.1	0.22	0.49	613
# Adult Equivalents (Pre-Landslide)	3.4	3.5	0.02	0.92	613
# Members Aged 0–5 (Pre-Landslide)	1.0	1.2	0.10	0.56	604
# Members Aged 6–17 (Pre-Landslide)	1.6	1.6	-0.02	0.91	604
# Members Aged 18–50 (Pre-Landslide)	1.7	1.6	0.10	0.54	604
# Members Aged 51 or older (Pre-Landslide)	0.4	0.4	-0.04	0.66	604
Large Farm (1 Acre or Larger, Pre-Landslide)	0.47	0.54	0.07	0.26	625
Farm Size (Acres, Pre-Landslide)	1.7	2.3	0.69***	0.00	625
Had Migrated Prior to Landslide	0.33	0.40	0.06	0.33	625
Had Family in Big City at Time of Landslide	0.49	0.52	0.07	0.23	625
Had Family in Kampala at Time of Landslide	0.27	0.29	0.06	0.28	625
Panel C: Retrospective Income and Welfare					
Income (Pre-Landslide)	33	35	-1.3	0.88	625
Income per Adult-Equivalent (Pre-Landslide)	12	15	1.1	0.82	625
Savings (Pre-Landslide)	38	57	12.3	0.21	625
Savings per Adult-Equivalent (Pre-Landslide)	12	20	5.3	0.20	625
Welfare Index (Pre-Landslide)	0.00	0.37	0.14	0.26	625

Notes: An observation is a household (based on pre-landslide structure). Columns 1 and 2 show means within unaffected and affected households, respectively. Column 3 shows the conditional difference recovered from a regression of each characteristic on an indicator for whether the household was affected, controlling for a landslide-event fixed effect plus the vector *Risk* containing geologic variables (Panel A excludes geographic controls). Columns 4 and 5 show p-values from Column 3 regressions testing for equal means and the number of observations. *Welfare Index* comprises 11 pre-landslide outcomes (see Section 4). Responses of "Don't Know" are coded as missing. Monetary units are USD/month. *** $p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.1 Destructive Impacts of Landslides

The landslides we study were highly destructive: households residing in a landslide path experienced extreme rates of death and property destruction. As shown in Panel A of Table 2, 45% percent of homes in a landslide path experienced major damage,[21] compared to 12% among homes outside the path ($p < 0.01$).[22] About 28% of affected households report casualties from the landslide (compared to 7% of unaffected households; $p < 0.01$), almost all of which represents death of a household member. Among affected households with casualties, the median number of casualties is 2 and the mean is 3.5. Both affected and unaffected households experienced damage to land, crops, livestock, or other possessions, although the rates are significantly higher among affected households. Affected households faced significant uncovered repair and reconstruction costs: these rise from an average of $177 among unaffected households to $503 among affected households ($p < 0.01$), representing over two years' worth of median household income.

3.2 Impacts on Displacement and Migration

Most households residing in a landslide path were displaced outside their home village, though a significant minority remained in the village. Panel A of Table 2 shows that even among unaffected households, 18% were displaced; this share rises to 68% among affected households ($p < 0.01$). 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. Only 28% of all affected households—just under half of displaced households—remain displaced outside their home village at the time of our survey in 2022. Among those that returned to their home village, about half were displaced for less than a year, one quarter were displaced for one year, and the rest were displaced for two or more years.

[21] 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.

[22] Damage to homes outside a landslide path is most likely due to heavy rains immediately preceding landslide events. There are several reasons why some of the homes that we categorize as residing in a landslide path were not damaged. Some homes, 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 a landslide path and those that are not reassures us that our measure is strongly correlated with true landslide exposure.

Table 2: Long-Run Impacts of Landslides

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.332***	0.214***	0.179***	0.240***	326***	0.496***	0.246***
	(0.056)	(0.049)	(0.056)	(0.037)	(72)	(0.054)	(0.045)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.12	0.07	0.52	0.72	177	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.113***	0.113***	0.008	0.090**	0.089**	0.003	-0.075*
	(0.041)	(0.038)	(0.029)	(0.040)	(0.036)	(0.022)	(0.042)
	[0.01]	[0.00]	[0.79]	[0.02]	[0.01]	[0.89]	[0.07]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.22	0.12	0.21	0.13	0.06	0.66
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.201***	0.121**	-0.401***	-0.348***	-0.194*	-0.083	-0.373***
	(0.059)	(0.059)	(0.120)	(0.113)	(0.113)	(0.110)	(0.110)
	[0.00]	[0.04]	[0.00]	[0.00]	[0.09]	[0.45]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00

Notes: An observation is a household (based on pre-landslide structure) in Panels A and C, and an individual aged 18 or older who was living in a pre-landslide household in Panel B. Migrants are individuals who live outside of the village where their household currently resides, or had left the village since the landslide to seek work and then returned; displacement of the household is not coded as migration. *Landslide* is an indicator equal to 1 if the household was located within 50 meters of a landslide path at the time of the landslide. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The landslides also increased migration among individuals in affected households. Panel B of Table 2 shows that individuals from affected households were 11 pp. more likely to migrate after the landslide (on a base of 31%; $p = 0.01$). All of these additional migrants traveled to a city, but almost none went to big cities. Most of this effect is driven by long-run migration: at the time of the survey, individuals from affected households are 9 pp. more likely to be urban migrants, almost doubling the baseline urban migration rate ($p = 0.01$).

3.3 Long-Run Impacts on Economic and Mental Health Outcomes

Landslides substantially worsen long-run economic and mental health outcomes, as shown in Panel C of Table 2.[23] To give three examples, affected household heads were 12 pp. more likely to report being seriously worried about their household finances (on a base of 51%, $p = 0.04$) and 20 pp. less likely to report being satisfied with their life in general (on a base of 54%, $p < 0.01$), and individuals from affected households were 8 pp. less likely to be economically active (on a base of 66%, $p = 0.07$). To provide coherent summaries of the landslides' long-run effects, we aggregate all of our survey information on economic and mental health outcomes into five indices constructed according to the methodology of Anderson (2008). We organize our survey information into four categories: financial health of the household, mental health of the respondent, home amenities, and income. We also construct an overall welfare index that includes all of these outcomes. We standardize all indices to have mean 0 and standard deviation (sd) 1 among unaffected households.

Across all five index measures, landslides have negative long-run impacts. The estimated impact on our financial health index is -0.4 sd ($p < 0.01$); on our mental health index it is -0.35 sd ($p < 0.01$); on our home amenity index it is -0.19 sd ($p = 0.09$); and on our income index it is -0.08 sd ($p = 0.45$). Our overall welfare summary index is lower by 0.37 sd ($p < 0.01$) among affected households.[24]

[23] We measure all outcomes at the time of the surveys, 3 to 12 years after the landslides.

[24] Appendix Table A2 shows impacts on each component of each index. 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 total household income over the past month (computed as the sum of earnings from household businesses over the

4 Which Mechanisms Are Driving Welfare Impacts?

What explains the landslides' large, persistent negative impacts on economic and mental health outcomes? Comparing our study to others in the literature reveals several major contextual differences which may explain our divergent results. First, affected households experienced a very high casualty rate. Second, the institutional capacity to insure households *ex ante* or distribute aid or assist with recovery *ex post* was low. As a result, many affected households were forcibly displaced outside of their home village. Many also turned to urban migration as a means to cope with the disaster. In this section, we examine the role of these mechanisms in driving welfare impacts, and find that the same factors that differ greatly between our context and those in the extant literature—especially casualties and displacement without government support—are also driving variation in welfare impacts in our data.

Casualties and Damage. The damage and death toll of the landslides were severe, causing casualties in 28% of households residing in their path (94% of these casualties were deaths) and substantial damage to 45% of homes. In Section 4.1, we examine the role of casualties and damage in explaining the welfare impacts of landslides, and find that these factors, especially casualties, play a major role. However, other disasters found to have positive long-run economic effects—such as the 2004 Indian Ocean tsunami—caused enormous death tolls and damages, suggesting that this is unlikely to be the sole factor.

Displacement, Return, and Resettlement Assistance. In our setting, in contrast to most other studies of natural disasters, a significant share of affected households were displaced from their home villages. Displacement could be disruptive *per se* if it imposes psychic costs that households don't recover from, or it may upset the location-specific knowledge and social capital that the displaced had built up. Governments or other aid agencies may be able to mitigate the negative

past month, earnings from individual salaries and wages over the past month, and crop production value from the most recent season converted to a monthly value), household non-farm income over the past year (computed as the sum of earnings from household businesses over the past year and earnings from individual salaries and wages over the past year), household savings over the past month, household food consumption over the past week, and the share of children who have been in school since the landslide. We divide household income, savings, and consumption by the number of adult-equivalents residing in the household at the time of the survey using World Food Programme consumption equivalence scales (Mathiassen et al., 2017).

impacts of displacement by providing resettlement assistance, and indeed in studies finding positive impacts of natural disaster the government played a significant role in coordinating recovery efforts and disbursing aid (Gignoux and Menéndez, 2016, Heger and Neumayer, 2019, Nakamura et al., 2021). In our setting, aid and government support were much more limited.[25] We consider the role of displacement in Section 4.2.

Migration. Natural disasters may improve economic outcomes if they encourage migration to locations with higher productivity (Deryugina et al., 2018) or that better match individuals' comparative advantages (Nakamura et al., 2021), a hypothesis we consider in Section 4.3. In contrast to predominantly rural household displacement, individual migration in response to landslides was entirely urban. Sectoral productivity gaps are substantial in most developing economies, including Uganda (Gollin et al., 2014), but gains from rural-to-urban migration may remain uncaptured due to frictions such as information failures (Baseler, 2023). However, it is unclear whether disaster-driven migration affords the same benefits as other migration.

Identification Challenges. To investigate the role of the above mechanisms in intermediating welfare impacts, we estimate (1) including controls for each channel, which we also interact with *Landslide*. Studying the mechanisms behind the negative welfare impacts of landslides introduces two additional challenges, especially because displacement and migration are likely choices made by households *ex-post*. First, if a potential channel—such as migration—is correlated with pre-landslide characteristics that are predictive of landslide impacts, then the differential welfare effects based on migration will reflect both the impact of migration as well as heterogeneity along those pre-landslide dimensions. For example, if wealthier households are better able to cope with landslide losses and also more likely to migrate afterward—possibly because they can afford the upfront migration cost—then our analysis would overstate the benefit of migrating. Second, the choice to relocate or migrate—as well as receipt of resettlement assistance—are likely to be directly affected by the extent of landslide damages, which could also directly affect long-run welfare. The first concern also applies, though likely to a lesser extent, to analyzing the role of casual-

[25]The average affected household received only $34 in aid—about 8% of damages—and the government managed only a minority of displacements to temporary resettlement camps. Landslide victims in Bududa have sued the Ugandan government over a lack of support (Wambede and Woniala, 2021), and reports by the Uganda Red Cross Society show how limited the response capabilities by government and civil society are (Uganda Red Cross Society, 2019).

ties and damage, since households may make investments to mitigate potential landslide damages (for example, planting trees), which could lead landslide damages conditional on exposure to be correlated with investment capabilities, even if landslide paths are as good as random.

We use two strategies to address the above challenges. The first is to analyze changes in welfare over time—from just before the landslide to the time of our survey—rather than differences in levels of measured welfare at the time of the survey. Specifically, we construct a summary index of pre-landslide welfare based on retrospective questions,[26] and compute the difference between the current and pre-landslide index values. Provided that displaced and non-displaced households were on similar welfare trends at the time of the landslide, pre-existing welfare differences will not influence our estimates. Our second strategy is to systematically control for pre-landslide characteristics that may be correlated with welfare impacts as well as with the channels we consider, and their interactions with *Landslide*. Because of the large number of variables we could potentially control for compared to the number of observations, we select these controls through lasso regression (Tibshirani, 1996, Belloni and Chernozhukov, 2013). Specifically, we predict each intermediating variable with the set of pre-landslide characteristics displayed in Table 1. When studying displacement and migration channels, we also include variables capturing the damages caused by the landslide.[27] For each pre-landslide or damage variable selected by the lasso regression, we include it, and its interaction with *Landslide*, as control variables. Appendix Table A3 shows the set of control variables selected. While these strategies mitigate the potential for other mechanisms to confound our estimates, the possibility of unobserved selection remains, and so the result in this section should not be viewed as conclusive.

4.1 The Role of Casualties and Damage

The medical literature studying the psychological harms of disaster emphasizes the role of traumatic experiences such as the sudden death of a family member (Norris et al., 2002, Porter and

[26] Although this could introduce concerns about recall bias, pre-landslide welfare is not significantly different between affected and unaffected households, as shown in Table 1 ($p = 0.26$). Our pre-landslide welfare index uses the same measures as our contemporary welfare index, except: number of friends, optimism about the future, experience of a recent financial emergency, pulling a child out of school, worry about finances, consumption, share of children in school, and yearly income. Monthly pre-landslide income excludes harvest value.

[27] Specifically, we include total uncovered repair costs, and indicators for whether the house was damaged, whether land was damaged, whether there were other damages, and whether there were any casualties, in addition to the set of variables shown in Table 1.

Haslam, 2005, Makwanam, 2019), and a growing literature in behavioral economics shows that mental health and economic outcomes are directly linked (Ridley et al., 2020). In our setting, households residing in a landslide path experienced very high rates of casualty and property loss, as shown in Table 2.

We find that property damage, and especially casualties among household members, are substantially predictive of negative welfare impacts, as shown in Table 3. We add several variables capturing casualties and property damage to our estimation of (1): indicators for whether the household experienced a casualty, damage to their house, damage to their land, and damage to other property. As shown in Column 1, households experiencing a casualty show a 0.65-standard-deviation decrease in our welfare index compared to households that did not, conditional on residing in a landslide path and other damages ($p < 0.01$). Damage to the house also predicts worse welfare impacts, by 0.24 sd ($p = 0.06$). Damage to land and other property also display negative effects, but of smaller magnitude. As shown in Column 2, these estimates are robust to controlling for pre-landslide characteristics that predict landslide damages.

Columns 3 and 4 of Table 3 add interaction terms between each measure of casualty or damage and $Landslide$. Households located in a landslide path experienced worse impacts along each damage measure than households reporting the same type of damage who resided outside a landslide path. The difference is particularly large for casualties, where welfare changes for households in a landslide path are 0.77 sd worse compared to households outside a path ($p = 0.02$). In column 3, the welfare change for households experiencing a casualty but located outside a path is negative, but smaller in magnitude (coeff. $= -0.32$ sd, $p = 0.13$). These results are robust to controlling for pre-landslide characteristics predictive of casualties or damages, and their interactions with $Landslide$, as shown in Column 4. These differences are not driven purely by an intensive-margin difference in the number of casualties among households hit by landslides: controlling for the number of casualties changes the estimated differences very little, as shown in column 5.

Table 3: Casualties and home destruction play a substantial role in explaining welfare outcomes.

	(1)	(2)	(3)	(4)	(5)
	Dep Var: Change in Welfare Index (Compared to Pre-Landslide)				
Landslide × Casualty			-0.771**	-0.849**	-0.780**
			(0.341)	(0.334)	(0.328)
			[0.02]	[0.01]	[0.02]
Landslide × Damage to Home			-0.115	-0.058	-0.045
			(0.327)	(0.328)	(0.328)
			[0.72]	[0.86]	[0.89]
Landslide × Damage to Land			-0.453	-0.589**	-0.559*
			(0.284)	(0.292)	(0.292)
			[0.11]	[0.04]	[0.06]
Landslide × Damage to Other Property			-0.585	-0.529	-0.551
			(0.580)	(0.485)	(0.484)
			[0.31]	[0.28]	[0.26]
Casualty	-0.647***	-0.618***	-0.318	-0.275	-0.127
	(0.176)	(0.174)	(0.210)	(0.215)	(0.260)
	[0.00]	[0.00]	[0.13]	[0.20]	[0.63]
Damage to House	-0.242*	-0.232*	-0.142	-0.167	-0.172
	(0.129)	(0.129)	(0.144)	(0.146)	(0.147)
	[0.06]	[0.07]	[0.32]	[0.25]	[0.24]
Damage to Land	-0.145	-0.059	-0.071	0.020	0.020
	(0.096)	(0.096)	(0.102)	(0.102)	(0.102)
	[0.13]	[0.54]	[0.49]	[0.84]	[0.84]
Damage to Other Property	-0.078	-0.029	-0.072	-0.011	-0.007
	(0.113)	(0.111)	(0.116)	(0.115)	(0.116)
	[0.49]	[0.79]	[0.54]	[0.92]	[0.96]
# of Casualties					-0.059
					(0.049)
					[0.23]
Landslide	-0.253*	-0.246*	0.789	-1.847	-1.842
	(0.140)	(0.142)	(0.575)	(1.943)	(1.930)
	[0.07]	[0.09]	[0.17]	[0.34]	[0.34]
Observations	625	625	625	625	625
Demographic Controls		X		X	X
Demographic × Landslide Controls				X	X

Notes: Dependent variable is the difference between current welfare index and a pre-landslide welfare index. Welfare indices combine measures of financial health, mental health, home amenities, and income (see Section 3.3 for a list of components) using the method of Anderson (2008). All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Column 2 includes all demographic controls that predict any of the casualty or damage variables, and Columns 4 and 5 include their interactions with *Landslide* (see Appendix Table A3 for a list of controls). Robust standard errors in parentheses; two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Interpretation. If differences in *Landslide* conditional on reporting a casualty were driven by measurement error—for example, originating in our GPS readings of households' pre-landslide locations—we would not expect to observe a greater welfare change among households residing in a landslide path. Instead, this result suggests that households find it particularly difficult to cope with casualties caused suddenly and directly by the landslides, compared to unrelated casualties that occurred around the time of the landslides, or casualties due to indirect effects such as through disruptions in economic activity.

The role of casualties in explaining our results may help reconcile our findings when compared to those of Chiovelli et al. (2021). Reliable data on deaths caused by the the Mozambican civil war are sparse, but the death rate among the displaced was certainly lower than in our setting, where 35% of displaced households experienced the death of a member due to the landslide, compared to 5% for non-displaced households outside a landslide path.[28] Most importantly, the death rate among the non-displaced was likely also high during the Mozambican civil war—possibly even higher than the rate among the displaced—whereas households residing outside a landslide path experienced a much lower death rate of around 6%.

4.2 The Role of Displacement

How does displacement contribute to the welfare impacts of landslides? Our setting is one of the few studied in the extant literature on natural disaster that involved a high rate of household displacement. Moreover, these moves largely represent forced displacement with little outside support. Among all households reporting that they were displaced by a landslide, 26% reported that the government organized the move, while the other 74% reported that they moved on their own. Among displaced households, the most common reason given for why they left the village is that their livelihood was destroyed. On the other hand, the most common reason given for staying in the village among the affected, non-displaced households is that they could not finance the relocation costs. The role of displacement in mediating welfare impacts is thus theoretically ambiguous.

[28] Estimates of the number of direct civilian killings range from early estimates as high as 100,000 (Gersony, 1988) to more recent, lower estimates of 829 (Weinstein and Francisco, 2005). Many more died of famines during the war, with an estimated number of total civilian deaths around 600,000 (Africa Watch, 1997). The number displaced was much higher, around four million (Chiovelli et al., 2021).

Table 4: Displacement and migration play a substantial role in explaining welfare outcomes.

Dep Var: Change in Welfare Index	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Landslide × Displaced	-0.656**	-0.602**	-0.813***	-0.728**	-0.331	-0.062		
	(0.291)	(0.274)	(0.311)	(0.292)	(0.507)	(0.498)		
	[0.02]	[0.03]	[0.01]	[0.01]	[0.51]	[0.90]		
Landslide × Displaced by Gov't			0.633**	0.485*	-0.163	-0.247		
			(0.302)	(0.278)	(0.436)	(0.406)		
			[0.04]	[0.08]	[0.71]	[0.54]		
Displaced	0.044	0.119	0.043	0.119	0.133	0.219		
	(0.135)	(0.140)	(0.135)	(0.140)	(0.247)	(0.241)		
	[0.75]	[0.40]	[0.75]	[0.40]	[0.59]	[0.36]		
Landslide × Returned to Village					-0.754	-0.934*		
					(0.517)	(0.487)		
					[0.14]	[0.06]		
Landslide × Returned from Gov't Displacement					1.434**	1.043*		
					(0.646)	(0.591)		
					[0.03]	[0.08]		
Returned to Village					-0.107	-0.116		
					(0.270)	(0.263)		
					[0.69]	[0.66]		
Landslide × # Urban Migrants							0.219**	0.323***
							(0.106)	(0.122)
							[0.04]	[0.01]
# Urban Migrants							-0.120***	-0.114***
							(0.037)	(0.042)
							[0.00]	[0.01]
Landslide	-0.061	1.174*	-0.058	1.180**	-0.061	0.873*	-0.704***	-0.439
	(0.202)	(0.599)	(0.202)	(0.600)	(0.204)	(0.525)	(0.198)	(0.326)
	[0.76]	[0.05]	[0.77]	[0.05]	[0.77]	[0.10]	[0.00]	[0.18]
Observations	625	625	625	625	625	625	625	625
Demographic + Demographic × Landslide Controls		X		X		X		X

Notes: Displaced = 1 if the household was displaced by a landslide, and *Returned to Village* = 1 if a displaced household later returned to the pre-landslide village. *# Urban Migrants* is the number of people who migrated to a city at some point after the landslide. Even-numbered columns include all demographic controls that predict any of the independent variables included in that regression, plus their interactions with *Landslide* (see Appendix Table A3 for a list of controls). Robust standard errors in parentheses; two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

We find that household displacement plays a substantial role in explaining welfare changes among affected households. As shown in Table 4, column 1, displaced households in a landslide path experienced a 0.66-sd greater decline in our index of welfare compared to displaced households outside a landslide path ($p = 0.02$). The coefficient on *Displaced* is small and positive, suggesting that displacement by households outside a landslide path was not as harmful, and possibly relatively voluntary. As shown in Column 2, this result is robust to controlling for other differential impacts of the landslides along dimensions that predict displacement.

Among displaced households in a landslide path, displacement required by the government appears to substantially mitigate negative welfare impacts compared to own displacement (coeff. = 0.63 sd, $p = 0.04$), as shown in Column 3. This finding is robust to controlling for other differential impacts of the landslides along dimensions that predict displacement or government-managed displacement, as shown in Column 4.

Among those displaced by landslides, those who later return to their home village experience pronounced negative welfare changes compared to those who remained outside their origin village.[29] The coefficient on this interaction is -0.75 sd ($p = 0.14$) in column 5, or -0.93 sd ($p = 0.06$) when controlling for differential landslide impacts based on pre-disaster characteristics in column 6. This difference disappears for returnees from government-managed displacement: the coefficient on the variable interacting *Landslide* with an indicator for returning from government-managed displacement is 1.4 sd ($p = 0.03$), or 1.0 sd ($p = 0.08$) when controlling for pre-landslide interactions.

Interpretation. That government-managed resettlement mitigates the negative displacement effects we observe offers a plausible explanation for the contrast between our results and those of other studies of natural disaster finding positive long-run effects, such as Gignoux and Menéndez (2016) and Heger and Neumayer (2019). In high-income countries, government agencies were substantially more involved in resettlement and reconstruction efforts: in the volcanic eruption studied in Nakamura et al. (2021), households were compensated for the value of their homes, and after Hurricane Katrina support from the National Guard and infrastructure reconstruction, aid,

[29] The majority of those who did not return remained in the destination to which they were initially displaced.

and insurance payments were massive (Deryugina et al., 2018).[30] Displaced Finnish communities studied in Sarvimäki et al. (2022) were given land and assistance establishing new farms. Even in the studies of natural disasters in developing countries, the aid receipts that followed were massive, in the case of the 2004 Indonesian tsunami exceeding estimated damages (Heger and Neumayer, 2019). External assistance was much rarer in our setting—as with most large natural disasters (see footnote 1)—but when provided appears to substantially mitigate long-run impacts.

The greater welfare drop among returnees compared to those who remain displaced is difficult to reconcile with the loss of origin-specific factors, such as location-specific knowledge, being the primary driver of welfare changes. Indeed, only about one-third of returnees reported a reason for returning that reflects an apparently 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. This suggests that displacement itself—whether when relocating due to the landslide or when returning afterward—creates long-run disruptions which households do not recover from even after several years. Alternatively, these findings could reflect that the households most negatively impacted by the landslides were the ones unable to establish themselves in the resettlement location. However, we do not observe a negative association between government-managed return and welfare changes, and controlling for factors predicting the decision to return does not affect our findings.

4.3 The Role of Urban Migration

The positive long-run impacts of displacement are thought to operate in part through place-based effects (Sacerdote, 2012, Nakamura et al., 2021, Chiovelli et al., 2021). Because many developing economies—including Uganda—are characterized by large spatial earnings gaps (Gollin et al., 2014), natural disasters could potentially increase income if they induce migration to high-income areas. As shown in Table 2, landslides substantially increased rural-urban migration.

What impact did migration have on affected households? We find that affected households that sent more migrants to cities after the landslide experienced a significantly attenuated welfare drop,

[30]Nakamura et al. (2021) find that displacement improves outcomes only for children—whereas older individuals were slightly worse off—which the authors interpret as consistent with reoptimizing education and career choices, which is harder for older individuals. Given that most households were displaced to similar, rural locations, the scope for such reoptimization is likely to be low in our setting.

compared to unaffected households, as shown in Column 7 of Table 4 (coeff. = 0.22 sd per urban migrant, $p = 0.04$).[31] This effect remains after controlling for pre-landslide characteristics that predict migration and their interactions with *Landslide*—in fact, the estimated effect rises to 0.32 sd ($p = 0.01$), consistent with negative selection into migrating—as shown in Column 8.

To understand better how selection is driving our estimates, we estimate selection-into-migration regressions separately among affected and unaffected households. If landslides induced higher-return individuals to migrate (relative to migrants from unaffected households), for example by lowering their relative utility from staying in the village, this could explain the positive coefficients shown in columns 7 and 8 of Table 4. In this case, we would expect to see more positive selection of migrants—along variables that predict destination earnings, such as schooling or past migration experience—from affected compared to unaffected households. Results are shown in Table 5. Our findings are not consistent with landslides' inducing higher-return individuals to migrate: if anything, urban migrants from affected households appear somewhat less positively selected compared to urban migrants from unaffected households. Across these two groups, the associations between urban migration and age, gender, and household size are statistically indistinguishable. However, selection into urban migration is less positive within affected households along education ($p = 0.19$), individual migration experience to the regional capital prior to the landslide ($p = 0.02$), pre-landslide welfare ($p = 0.02$), and an indicator for having family living in the capital at the time of the landslide ($p = 0.01$).

Interpretation. Our finding that individuals induced to migrate by landslides are less positively selected compared to other migrants from the same area is consistent with many studies of forced migration.[32] These patterns are suggestive of disaster-induced migration being used as a coping device.

Our finding that urban migration appears to mitigate the harmful impacts of landslides—despite less positive selection of disaster-induced migrants—suggests that the marginal return to rural-

[31] Among unaffected households, urban migration is associated with a decline in welfare (coeff. = -0.12 sd, $p < 0.01$), suggesting that individuals migrate in response to negative shocks.

[32] See, for example, Cortes (2004), Chin and Cortes (2015), and Dustmann et al. (2017). Forced migrants may also be relatively positively selected in contexts where the value of home amenities reduces emigration among the well-off (Abramitzky et al., 2022) or when persecution threatens income or wealth directly (Aksoy and Poutvaara, 2021). In general, the sign of migrant selection is likely to depend on wealth: see Bazzi (2017).

Table 5: Impact of Landslide on Selection Into Migration

Outcome: Individual is an Urban Migrant	(1) Coefficient (Unaffected)	(2) Coefficient (Affected)	(3) Difference (2–1)	(4) p-Value on Difference	(5) N
Individual Characteristics					
Age (Years)	-0.003	-0.003	-0.000	0.97	1,814
Female	0.037	0.074	0.037	0.48	1,814
Education (Years)	0.016	0.003	-0.013	0.19	1,814
Had Migrated Before Landslide	-0.065	-0.078	-0.013	0.87	1,814
Had Migrated to City Before Landslide	-0.061	-0.069	-0.008	0.92	1,814
Had Migrated to Big City Before Landslide	-0.054	-0.132	-0.078	0.31	1,814
Had Migrated to Mbale Before Landslide	-0.107	-0.231	-0.124**	0.02	1,814
Had Migrated to Kampala Before Landslide	-0.019	0.042	0.061	0.72	1,814
Had Migrated to Nairobi Before Landslide	-0.074	-0.226	-0.152***	0.00	1,814
Household Characteristics					
Household Size (Pre-Landslide)	0.011	0.019	0.009	0.57	1,814
# Adult Equivalents (Pre-Landslide)	0.023	0.034	0.012	0.52	1,814
Large Farm (1 Acre or Larger, Pre-Landslide)	0.062	-0.017	-0.079	0.32	1,814
Farm Size (Acres, Pre-Landslide)	0.029	-0.001	-0.030	0.23	1,814
Anyone Had Migrated Before Landslide	0.009	-0.001	-0.011	0.88	1,814
Had Family in Big City at Time of Landslide	0.043	0.048	0.006	0.94	1,814
Had Family in Kampala at Time of Landslide	0.049	-0.113	-0.162**	0.01	1,814
Income (Pre-Landslide)	0.007	0.027	0.020	0.63	1,814
Income per Adult-Equivalent (Pre-Landslide)	-0.027	-0.036	-0.009	0.91	1,814
Savings (Pre-Landslide)	0.018	0.005	-0.013	0.78	1,814
Savings per Adult-Equivalent (Pre-Landslide)	-0.000	-0.089	-0.089	0.31	1,814
Welfare Index (Pre-Landslide)	0.023	-0.049	-0.072**	0.02	1,814

Notes: An observation is an individual residing in a pre-landslide household. Columns 1 and 2 show coefficients from regressions of each characteristic on an indicator for whether the individual is an urban migrant, an indicator for whether the household was hit by a landslide, and the interaction of those two variables. Columns 3 and 4 show the difference in coefficients for affected compared to unaffected households and the p-value on that difference, respectively. All regressions control for a landslide-event fixed effect and geologic controls, and cluster standard errors at the household level. Currency units are 100s of USD/month. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

urban migration is positive in this context, at least for households affected by landslides. This is consistent with the literature showing that migration can help households cope with negative weather shocks, including natural disasters (Yang and Choi, 2007, Yang, 2008, Blumenstock et al., 2016, Mahajan and Yang, 2020). However, the finding that overall welfare and employment effects are nevertheless significantly negative indicates that the benefits of migrating are not high enough to offset the negative impacts of landslides.

4.4 Potential Alternative Explanations

In this section, we consider potential alternative explanations for our results, including measurement error in which households were affected, impacts on nearby households such as through general equilibrium effects, differential risk mitigation, and differential non-response, and argue that they are unlikely to be driving our findings.

Measurement Error in Identifying Affected Households. As discussed in Section 2.3, our preferred method for classifying households into directly affected or unaffected by the landslides involves overlaying landslide paths traced using satellite imagery with GPS readings taken at households' pre-landslide locations, as identified by the household members together with local leaders, and allowing for a 50-meter buffer to account for rubble or destabilized land not visible from satellite images. The large differences in casualty and destruction rates between these two groups reported in Table 2 support this method, as does the strong relationship between destruction rates and measured distance from the landslide site shown in Appendix Figure A1. Nevertheless, we consider two alternative classification methods: i) omitting the 50-meter buffer, and ii) using household survey reports of damage to their home during the landslide. Our impact estimates are robust to these alternative measures, as shown in Appendix Tables A4 and A5.

Impacts on Nearby Households. Our identification strategy uses nearby households, which we show were exposed to similar levels of landslide risk but were not directly impacted by landslides. It is likely, however, that our comparison group was indirectly affected by the landslides. For example, around half of households we classify as unaffected report that some of their land was damaged during the landslide. There are also likely to be disruptions to economic activity resulting from school or health clinic closures, road closures, and market disruptions. To the extent that these broader market effects have dissipated by the time of our surveys, 3–12 years after the landslides, they should not significantly affect our results. Moreover, any economic disruptions in our comparison group will lead us to understate the overall negative impacts of landslides on affected households.[33]

[33]We find it implausible that our comparison group benefited so much from landslides that welfare impacts were positive on average. The literature on natural disasters has highlighted two mechanisms through which directly or indirectly affected households can benefit: displacement to more advantageous locations, and aid. In our setting

To further explore whether impacts on nearby households residing outside of a landslide path are driving our results, we consider two proxies likely to capture indirect effects: whether the household resided nearby—outside of the 50-meter buffer, but within 1 kilometer of—a landslide site, and whether a landslide hit any households within the same village. Provided that indirect effects of landslides are stronger closer to the landslide site, or within the same village as the households that were hit, we expect these proxies to capture the most important indirect effects. We then estimate direct and indirect welfare effects of landslides by using completely unaffected households as a comparison group, with the caveat that our identifying assumptions are less likely to hold when comparing indirectly affected to completely unaffected households. To partly mitigate this concern, we include the full set of pre-landslide geological and demographic controls when estimating indirect effects.

We find that nearby and same-village households look largely similar on our welfare index to far-away households, or to households in villages with no landslides, respectively. As shown in column 7 of Appendix Table A11, our welfare index is 0.07 sd lower among households within 1 km of a landslide site, or 0.12 sd higher among households with a landslide in the village, and neither difference is statistically significant at the 10% level. These differences are swamped by the welfare difference between directly affected and indirectly affected households, and we can reject that the "total effect" of the landslides on our welfare index—that is, the sum of the direct and indirect welfare effects—is equal to zero at the 1% level. Appendix Table A12 replicates this analysis on the broader sample including Manafwa and Sironko districts, with very similar results. We conclude that our key findings are highly unlikely to be explained by impacts on the comparison group.

Differential Risk Mitigation. Even if our comparison group faced similar risks of being hit by a landslide—as our analysis indicates—it may still be that some households invest in landslide-mitigation technologies which influence the degree of landslide damages conditional on residing in the path of the landslide. Note that these investments are not a threat to our identification of welfare impacts unless they are correlated with *Landslide*, and our analysis—together with local reports (see footnote 16)—indicates that exact landslide paths are unpredictable. However, if these

displacement appears to worsen the impacts of landslides, and aid receipts were very small compared to damages.

investment decisions are a function of pre-landslide characteristics that also influence how households cope with the landslides' effects, this would complicate our mechanisms analysis. However, the robustness of that analysis to a principled set of controls—including landslide damages, which mitigation technologies would most directly affect—provides some reassurance that other pre-landslide characteristics such as risk mitigation are not responsible for our findings.

Differential Non-Response of Displaced Households. While our overall survey rate among households living in our study regions at the time of the landslide was very high, we were less likely to successfully survey households which had moved away from their home village after the landslide, as shown in Appendix Table A1. Our survey rate for households still residing in the origin was 94.4%; for households that had moved away it was 78.3%. To test whether this differential survey rate is influencing our results, we reproduce our main results weighting observations by the inverse probability of being surveyed, estimated by lasso logistic regression. Results, shown in Appendix Table A10, are extremely similar to unweighted results. We conclude that differential attrition is not a significant factor in this study. Moreover, we note that a conventional study design would not have surveyed any households that had relocated prior to sampling; our study thus offers a rare opportunity to analyze the impact of disaster and displacement on the full affected population with modest non-response even among the displaced.

5 Discussion

Natural disasters displace millions of people a year, but are difficult to study because displacement complicates the collection of reliable data on affected populations, and because people tend to sort out of high-risk areas. Most studies of natural disasters involving significant displacement also focus on developed countries with compensation schemes and welfare nets, although most displacement occurs in developing countries. We overcome these challenges by combining information on exact landslide paths and pre-existing landslide risk—which together 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 full affected population. Extensive tracking

of relocated households made this possible in a setting with high rates of displacement. This study thus offers what we believe is the first rigorous economic analysis of the household-level impact of a natural disaster that caused high rates of death and displacement but where victims received little aid or assistance. Aid receipts in our setting were typical of large natural disasters in developing countries, which increases the generalizability of these results.

We find that landslide-affected households were more likely to be displaced to a rural location, more likely to send migrants to urban locations, less likely to have economically active members, and appear significantly worse off along several economic and mental health dimensions. The negative impacts on welfare are pronounced among households that were displaced by the landslide, although government resettlement administration and urban migration appear to attenuate negative impacts. This may explain why other studies of natural disasters—which study contexts in which displacement is rare or the government or civil society actors provided substantial humanitarian and development aid—often find small or even positive long-run economic impacts.

In studies of natural disasters involving significant displacement, the economic benefits of displacement appear to be due to location-specific advantages at the destination (Deryugina et al., 2018, Nakamura et al., 2021). In our setting, most displaced households moved to villages and rural relocation centers throughout eastern Uganda, which are unlikely to offer locational advantages relative to households' home villages. Our findings, together with those of the extant literature, thus point to the importance of the destination in determining long-run outcomes for the displaced. We also find that casualties within the household worsen the impact of the disaster. This is perhaps unsurprising, but it should be noted that such casualties are much rarer in developed-country settings. Taken together, our findings indicate that the positive economic impacts of displacement observed in the economic literature are unlikely to apply to many low-income settings.

The Ugandan government has long considered permanent relocation of households living in areas at risk of landslides, but thousands of households continue to reside in these areas. While the findings of this study bolster calls for resettlement, we note that no study we are aware of has estimated the impact of pre-landslide resettlement. In addition to better understanding the value of *ex-ante* relocation, future work could help to identify who would benefit most from *ex-post* resettlement in the event that *ex-ante* resettlement is not possible or not desirable, and help to understand the factors contributing to successful resettlement efforts.

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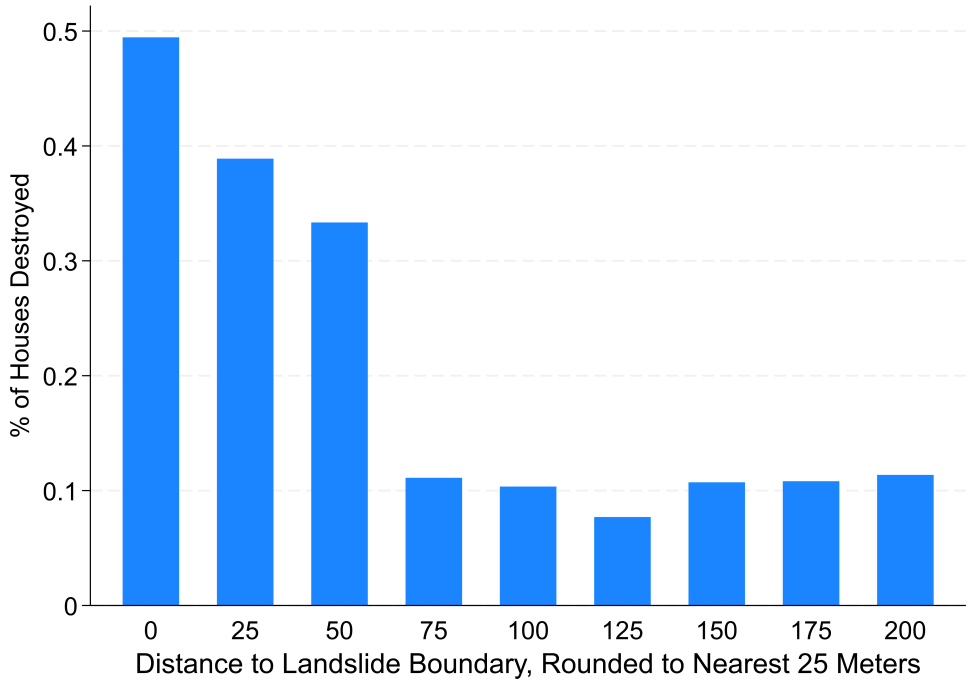
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Online Appendix for "Disastrous Displacement: The Long-Run Impacts of Landslides" by Travis Baseler and Jakob Hennig

A Additional Tables and Figures

Figure A1: Reported Home Destruction Rate, by Distance to Landslide Boundary



Notes: Houses located within the boundary coded as distance = 0. Distance rounded to nearest 25 meters.

Table A1: Tests of Selection Into Survey Sample

	(1)	(2)	(3)	(4)	(5)
	Dep Var: Surveyed = 1				
Age of Household Head (Years)	0.001				0.001
	(0.001)				(0.001)
	[0.24]				[0.31]
Household Size		0.003			0.003
		(0.004)			(0.004)
		[0.34]			[0.47]
Currently Displaced = 1			-0.162***		-0.159***
			(0.038)		(0.038)
			[0.00]		[0.00]
Bushika Event = 1				-0.017	-0.020
				(0.028)	(0.029)
				[0.56]	[0.49]
Buwali Event = 1				0.012	0.008
				(0.025)	(0.026)
				[0.63]	[0.75]
Nametsi Event = 1				-0.047	-0.050*
				(0.030)	(0.030)
				[0.11]	[0.09]
Observations	663	672	675	675	663

Notes: An observation is a household located in Bududa prior to the landslides we study. Each column shows a regression of an indicator for whether the household was surveyed on one or more administrative variables. *Currently Displaced* indicates that the household is listed as residing in a different village than it was before the landslide. Age and household size are missing from a small number of administrative records. Robust standard errors in parentheses; two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A2: Impacts on Individual Welfare Measures

Panel A: Financial Health	(1) Enough Food	(2) Can Pay Expenses	(3) No Financial Emergency	(4) No Education Disruption	(5) Not Worried About Finances	(6) Robust to Financial Shock
Landslide	-0.101*	-0.106*	-0.078	-0.091	-0.121**	-0.127**
	(0.054)	(0.059)	(0.053)	(0.065)	(0.059)	(0.059)
	[0.06]	[0.07]	[0.14]	[0.16]	[0.04]	[0.03]
Observations	623	608	609	526	606	624
Dep Var Mean for Landslide = 0	0.76	0.58	0.76	0.57	0.49	0.46
Panel B: Mental Health	Usually Happy	Usually Not Nervous	Satisfied With Life	Optimistic About Life		
Landslide	-0.071	-0.141**	-0.201***	-0.014		
	(0.059)	(0.060)	(0.059)	(0.061)		
	[0.23]	[0.02]	[0.00]	[0.81]		
Observations	625	609	608	604		
Dep Var Mean for Landslide = 0	0.64	0.55	0.54	0.42		
Panel C: Amenities	Improved Toilet	Improved Drinking Water	Improved Cooking Fuel	Residence is Safe	Number of Close Friends	
Landslide	-0.049*	-0.041	0.014	-0.054	-0.157	
	(0.028)	(0.039)	(0.010)	(0.050)	(0.517)	
	[0.07]	[0.30]	[0.16]	[0.28]	[0.76]	
Observations	625	625	625	625	625	
Dep Var Mean for Landslide = 0	0.06	0.11	0.00	0.81	4.89	
Panel D: Income	Total Income, Past Month	Non-Farm Income, Past Year	Savings, Past Month	Food Spending, Past Week	% Children in School	
Landslide	-4.82	-66.85***	-5.73	0.34	0.02	
	(12.88)	(24.12)	(3.84)	(0.83)	(0.05)	
	[0.71]	[0.01]	[0.14]	[0.68]	[0.65]	
Observations	625	625	569	625	454	
Dep Var Mean for Landslide = 0	49.68	131.49	14.30	5.85	0.75	

Notes: An observation is a household (based on pre-landslide structure). Each panel shows impacts on components of the welfare indices used in Table 2 Panel C. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Currency units are USD per month. Robust standard errors in parentheses. Two-sided p-values in brackets. See Section 3.3 for variable definitions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A3: Selected Pre-Landslide Predictor Variables in Lasso Regressions, by Mechanism

	(1) Casualty	(2) House Damaged	(3) Land Damaged	(4) Any Other Damage	(5) Displaced	(6) Displaced by Gov't	(7) Returned to Village	(8) # Urban Migrants
Elevation (Kilometers)	0.46							
Unstable Upslope Area (% of total)		-0.54						
Household Size (Pre-Landslide)				0.01				
# Adult Equivalents (Pre-Landslide)								0.18
# Members Aged 6–17 (Pre-Landslide)				0.03				
# Members Aged 18–50 (Pre-Landslide)								0.19
Large Farm (1 Acre or Larger, Pre-Landslide)			0.11					
Farm Size (Acres, Pre-Landslide)			0.06					
Had Migrated Prior to Landslide								0.31
Savings (Pre-Landslide)			0.09	0.06				
Casualty					0.19			
House Damaged					0.37		0.25	
Any Other Damage					0.11		0.09	
Observations	625	625	625	625	625	625	625	625

Notes: An observation is a household located in Bududa prior to the landslides we study. Each column shows OLS coefficients selected from a lasso regression of a mechanism of interest on the set of pre-landslide characteristics displayed in Table 1. Savings measured in 100s of USD.

Table A4: Impact estimates are robust to defining affected households using exact landslide path (without a 50 meter buffer).

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide (No Buffer)	0.328***	0.236***	0.240***	0.240***	232**	0.520***	0.336***
	(0.079)	(0.079)	(0.075)	(0.046)	(103)	(0.068)	(0.074)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.15	0.08	0.53	0.74	203	0.22	0.04
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide (No Buffer)	0.066	0.060	-0.009	0.016	0.006	-0.022	-0.052
	(0.058)	(0.052)	(0.038)	(0.056)	(0.043)	(0.023)	(0.058)
	[0.26]	[0.25]	[0.82]	[0.77]	[0.90]	[0.34]	[0.37]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.32	0.23	0.13	0.23	0.14	0.07	0.65
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide (No Buffer)	-0.259***	0.023	-0.251	-0.338**	-0.177	-0.216	-0.394**
	(0.084)	(0.086)	(0.174)	(0.163)	(0.168)	(0.161)	(0.156)
	[0.00]	[0.79]	[0.15]	[0.04]	[0.29]	[0.18]	[0.01]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.53	0.52	-0.03	-0.02	-0.02	0.00	-0.03

Notes: Landslide (No Buffer) = 1 if the household was located within an exact landslide path at the time of the landslide. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided *p*-values in brackets. ***p< 0.01, **p< 0.05, *p< 0.1.

Table A5: Impact estimates are robust to defining affected households using self-reported damages.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
House Damaged	-	0.210***	0.169***	0.217***	555***	0.384***	0.151***
	-	(0.043)	(0.051)	(0.033)	(76)	(0.049)	(0.038)
	-	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	-	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	-	0.06	0.52	0.72	123	0.19	0.04
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
House Damaged	0.078**	0.046	-0.030	0.051	0.012	-0.041**	-0.018
	(0.038)	(0.034)	(0.022)	(0.038)	(0.031)	(0.014)	(0.035)
	[0.04]	[0.18]	[0.17]	[0.18]	[0.70]	[0.00]	[0.60]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.23	0.13	0.22	0.14	0.07	0.65
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
House Damaged	-0.265***	0.160***	-0.417***	-0.446***	-0.035	-0.095	-0.352***
	(0.052)	(0.053)	(0.103)	(0.104)	(0.107)	(0.088)	(0.093)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.74]	[0.28]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.56	0.49	0.02	0.03	-0.02	0.01	0.01

Notes: House Damaged = 1 if the the respondent reported that their home was damaged from a landslide. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A6: Impact estimates are robust to controlling for pre-landslide household characteristics.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.332***	0.209***	0.159***	0.214***	294***	0.476***	0.252***
	(0.057)	(0.048)	(0.056)	(0.039)	(70)	(0.055)	(0.045)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.12	0.07	0.52	0.72	177	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.071*	0.080**	-0.006	0.046	0.053	-0.008	-0.065*
	(0.040)	(0.037)	(0.030)	(0.038)	(0.032)	(0.023)	(0.037)
	[0.08]	[0.03]	[0.85]	[0.23]	[0.10]	[0.72]	[0.07]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.22	0.12	0.21	0.13	0.06	0.66
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.202***	0.105*	-0.394***	-0.357***	-0.245**	-0.128	-0.422***
	(0.062)	(0.062)	(0.123)	(0.116)	(0.115)	(0.103)	(0.108)
	[0.00]	[0.09]	[0.00]	[0.00]	[0.03]	[0.21]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00

Notes: All regressions include a landslide-event fixed effect, geologic controls at the pre-landslide location, and pre-landslide demographic controls. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A7: Impact estimates are robust to excluding geographic controls.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.325***	0.215***	0.171***	0.220***	275***	0.500***	0.236***
	(0.054)	(0.048)	(0.054)	(0.033)	(69)	(0.051)	(0.044)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.13	0.07	0.52	0.72	177	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.105***	0.109***	0.013	0.080**	0.084**	0.005	-0.064
	(0.040)	(0.037)	(0.028)	(0.039)	(0.035)	(0.021)	(0.041)
	[0.01]	[0.00]	[0.64]	[0.04]	[0.02]	[0.81]	[0.12]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.22	0.12	0.21	0.13	0.06	0.66
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.171***	0.106*	-0.329***	-0.290***	-0.192*	-0.083	-0.330***
	(0.057)	(0.057)	(0.121)	(0.110)	(0.116)	(0.103)	(0.106)
	[0.00]	[0.07]	[0.01]	[0.01]	[0.10]	[0.42]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00

Notes: All regressions include a landslide-event fixed effect. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. ***p¡0.01,$^{**}p < 0.05$, $^{*}p < 0.1$.

Table A8: Impact estimates are robust to restricting to a sample with common support of pre-landslide elevation, farm size, and distance from nearest unstable point.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.340***	0.213***	0.153**	0.263***	288***	0.492***	0.237***
	(0.060)	(0.050)	(0.061)	(0.046)	(80)	(0.060)	(0.045)
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	453	453	453	453	453	453	453
Dep Var Mean for Landslide = 0	0.11	0.06	0.51	0.69	154	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.119***	0.119***	0.006	0.092**	0.095**	0.006	-0.033
	(0.043)	(0.041)	(0.031)	(0.043)	(0.038)	(0.025)	(0.046)
	[0.01]	[0.00]	[0.85]	[0.03]	[0.01]	[0.83]	[0.48]
Observations	1,292	1,292	1,292	1,292	1,292	1,292	1,292
Dep Var Mean for Landslide = 0	0.31	0.21	0.13	0.22	0.12	0.06	0.64
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.218***	0.078	-0.318**	-0.380***	-0.106	-0.099	-0.331**
	(0.064)	(0.064)	(0.127)	(0.125)	(0.120)	(0.147)	(0.133)
	[0.00]	[0.22]	[0.01]	[0.00]	[0.38]	[0.50]	[0.01]
Observations	440	438	453	453	453	453	453
Dep Var Mean for Landslide = 0	0.54	0.49	0.00	-0.02	-0.05	0.00	-0.03

Notes: Unaffected household sample restricted to households with common support across affected and unaffected groups for pre-landslide elevation, distance to nearest unstable point, and farm size. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A9: Impact estimates are similar in a broader sample including Bududa, Manafwa, and Sironko districts.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.371***	0.167***	0.173***	0.212***	156***	0.483***	0.318***
	(0.044)	(0.036)	(0.044)	(0.029)	(53)	(0.041)	(0.039)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	912	912	912	912	912	912	912
Dep Var Mean for Landslide = 0	0.17	0.06	0.53	0.73	217	0.22	0.05
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.054	0.052*	-0.016	0.042	0.038	-0.013	-0.028
	(0.033)	(0.030)	(0.021)	(0.031)	(0.028)	(0.016)	(0.031)
	[0.10]	[0.09]	[0.46]	[0.18]	[0.17]	[0.42]	[0.37]
Observations	2,683	2,683	2,683	2,683	2,683	2,683	2,683
Dep Var Mean for Landslide = 0	0.33	0.23	0.12	0.23	0.14	0.07	0.67
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.119**	0.059	-0.309***	-0.179*	0.036	-0.091	-0.185**
	(0.048)	(0.047)	(0.102)	(0.092)	(0.114)	(0.076)	(0.093)
	[0.01]	[0.22]	[0.00]	[0.05]	[0.75]	[0.23]	[0.05]
Observations	891	888	912	912	912	909	912
Dep Var Mean for Landslide = 0	0.54	0.50	-0.01	-0.03	0.10	0.00	0.03

Notes: Sample includes two additional landslide events in Manafwa and Sironko districts, where geologic data are not available. All regressions include a landslide-event fixed effect and pre-landslide demographic and elevation controls. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A10: Impact estimates are robust to reweighting observations to account for predicted non-response.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.332***	0.214***	0.179***	0.240***	326***	0.496***	0.246***
	(0.056)	(0.049)	(0.056)	(0.037)	(72)	(0.054)	(0.045)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.12	0.07	0.52	0.72	177	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.113***	0.113***	0.008	0.090**	0.089**	0.003	-0.075*
	(0.041)	(0.038)	(0.029)	(0.040)	(0.036)	(0.022)	(0.042)
	[0.01]	[0.00]	[0.79]	[0.02]	[0.01]	[0.89]	[0.07]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.22	0.12	0.21	0.13	0.06	0.66
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.201***	0.121**	-0.401***	-0.348***	-0.194*	-0.083	-0.373***
	(0.059)	(0.059)	(0.120)	(0.113)	(0.113)	(0.110)	(0.110)
	[0.00]	[0.04]	[0.00]	[0.00]	[0.09]	[0.45]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00

Notes: Observations are weighted by the inverse of the probability of being surveyed, estimated on administrative household data through logit lasso regression. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A11: Indirect effects of landslides on nearby households appear too small to explain our main results.

Panel A: Indirect Effects Within 1 Km of Site	(1) Satisfied With Life	(2) Worried About Finances	(3) Financial Health Index	(4) Mental Health Index	(5) Home Amenity Index	(6) Income Index	(7) Overall Welfare Index
Landslide	-0.207***	0.127**	-0.403***	-0.341***	-0.196*	-0.151	-0.412***
	(0.062)	(0.062)	(0.125)	(0.118)	(0.115)	(0.104)	(0.109)
	[0.00]	[0.04]	[0.00]	[0.00]	[0.09]	[0.15]	[0.00]
Landslide Within 1 Km	0.036	-0.161**	0.060	-0.120	-0.350**	0.164	-0.074
	(0.075)	(0.068)	(0.139)	(0.143)	(0.150)	(0.112)	(0.122)
	[0.63]	[0.02]	[0.66]	[0.40]	[0.02]	[0.14]	[0.54]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00
p-Val: Landslide + Landslide Within 1 Km = 0	0.06	0.68	0.05	0.01	0.00	0.93	0.00
Panel B: Indirect Effects Within Village	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.224***	0.109	-0.452***	-0.289**	-0.281**	-0.214*	-0.481***
	(0.066)	(0.067)	(0.134)	(0.124)	(0.118)	(0.121)	(0.121)
	[0.00]	[0.11]	[0.00]	[0.02]	[0.02]	[0.08]	[0.00]
Landslide Within Village	0.136***	-0.088*	0.259**	0.036	-0.157	0.158*	0.118
	(0.049)	(0.048)	(0.101)	(0.100)	(0.097)	(0.088)	(0.093)
	[0.01]	[0.07]	[0.01]	[0.72]	[0.10]	[0.07]	[0.21]
Observations	600	598	605	605	605	605	605
Dep Var Mean for Landslide = 0	0.54	0.51	0.01	0.00	-0.01	0.00	0.00
p-Val: Landslide + Landslide Within Village = 0	0.21	0.76	0.17	0.06	0.00	0.59	0.00

Notes: All regressions include a landslide-event fixed effect, geologic controls at the pre-landslide location, and pre-landslide demographic controls. *Landslide Within 1 Km* = 1 if the household was located within 1 kilometer of any landslide site. *Landslide Within Village* = 1 if any household in the same village was directly affected by a landslide. Robust standard errors in parentheses. Two-sided *p*-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A12: Indirect effects of landslides on nearby households appear too small to explain our main results (broader sample including Bududa, Manafwa, and Sironko districts).

Panel A: Indirect Effects Within 1 Km of Site	(1) Satisfied With Life	(2) Worried About Finances	(3) Financial Health Index	(4) Mental Health Index	(5) Home Amenity Index	(6) Income Index	(7) Overall Welfare Index
Landslide	-0.113**	0.041	-0.322***	-0.188**	-0.016	-0.113	-0.236***
	(0.049)	(0.049)	(0.101)	(0.093)	(0.110)	(0.076)	(0.090)
	[0.02]	[0.41]	[0.00]	[0.04]	[0.89]	[0.14]	[0.01]
Landslide Within 1 Km	-0.004	-0.063	-0.027	-0.120	-0.389***	0.083	-0.165
	(0.062)	(0.060)	(0.120)	(0.118)	(0.135)	(0.089)	(0.103)
	[0.95]	[0.29]	[0.82]	[0.31]	[0.00]	[0.35]	[0.11]
Observations	886	883	904	904	904	904	904
Dep Var Mean for Landslide = 0	0.54	0.50	-0.01	-0.03	0.10	0.00	0.03
p-Val: Landslide + Landslide Within 1 Km = 0	0.12	0.76	0.02	0.03	0.01	0.78	0.00
Panel B: Indirect Effects Within Village	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.124**	0.037	-0.373***	-0.149	-0.071	-0.168*	-0.293***
	(0.052)	(0.052)	(0.108)	(0.097)	(0.117)	(0.087)	(0.101)
	[0.02]	[0.47]	[0.00]	[0.13]	[0.54]	[0.05]	[0.00]
Landslide Within Village	0.127***	-0.087**	0.260***	0.037	-0.139*	0.111	0.098
	(0.044)	(0.043)	(0.088)	(0.089)	(0.084)	(0.084)	(0.085)
	[0.00]	[0.04]	[0.00]	[0.68]	[0.10]	[0.19]	[0.25]
Observations	872	869	878	878	878	878	878
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	-0.03	0.09	0.00	0.02
p-Val: Landslide + Landslide Within Village = 0	0.96	0.39	0.36	0.33	0.09	0.47	0.06

Notes: All regressions include a landslide-event fixed effect and pre-landslide demographic controls plus elevation. *Landslide Within 1 Km* = 1 if the household was located within 1 kilometer of any landslide site. *Landslide Within Village* = 1 if any household in the same village was directly affected by a landslide. Robust standard errors in parentheses. Two-sided *p*-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

B Data Collection

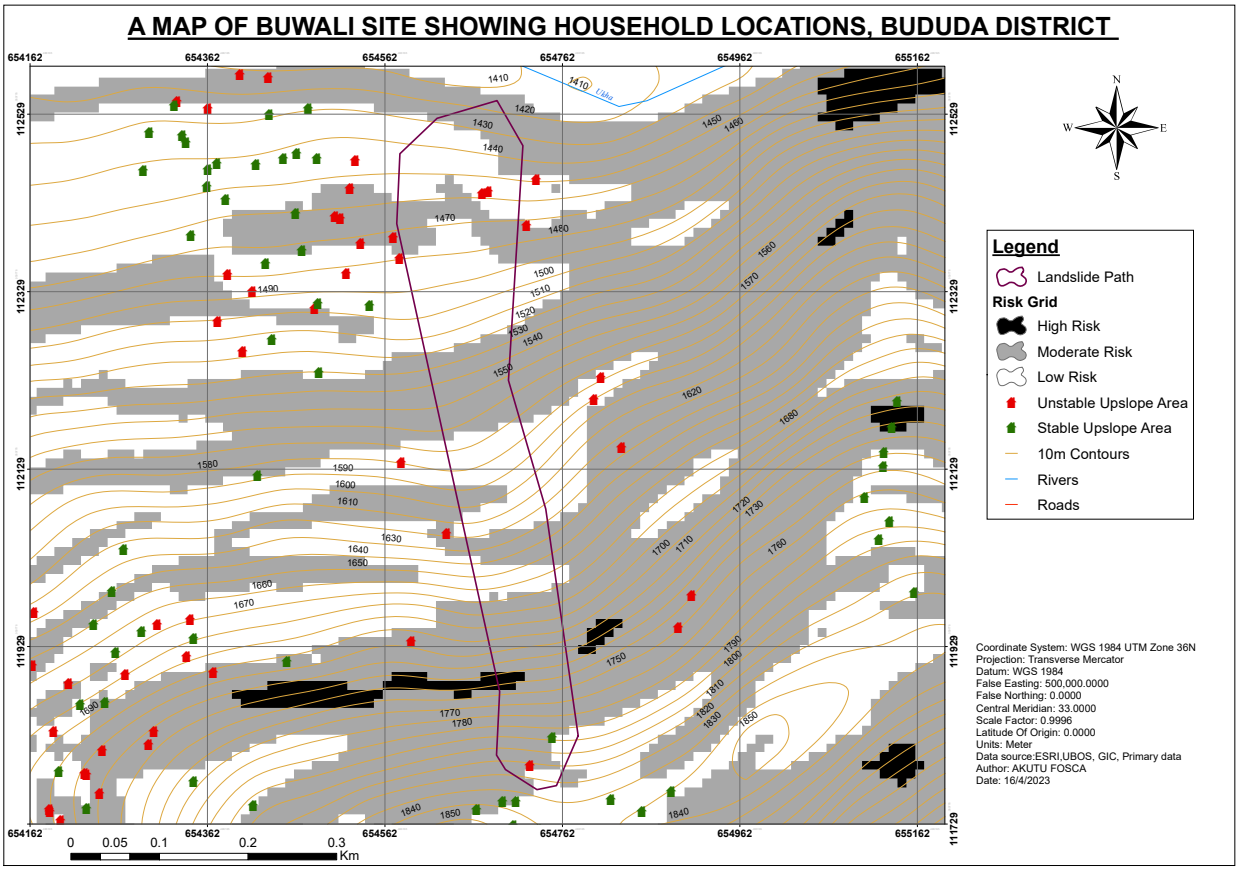
To identify sites for our study, we worked together with local leaders with insight into recent landslide events. They advised us on the sites of the largest landslides in the last 10 years, and shared lists of households that resided in villages in or near these sites at the time of the event. These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

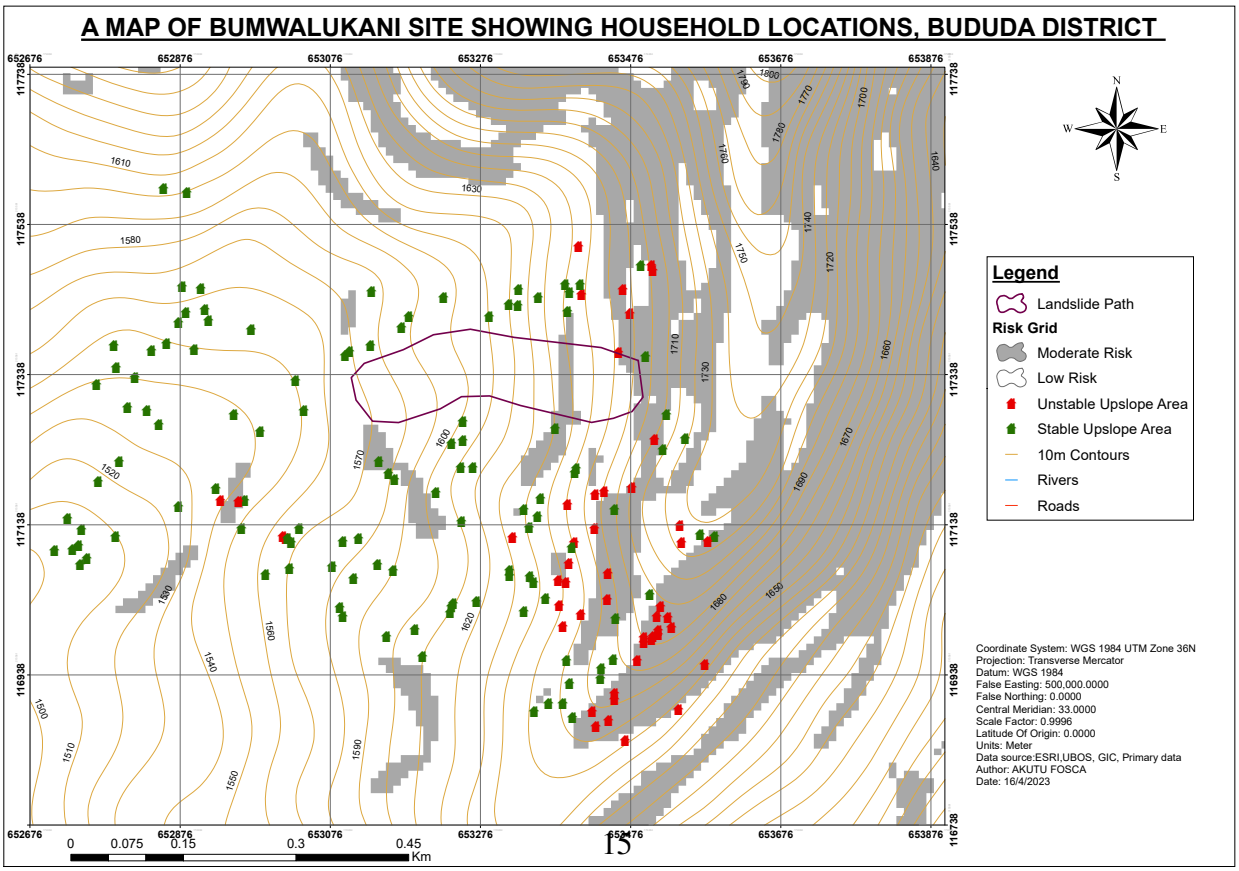
For each of these landslide sites, we established the extent of the survey perimeter by identifying directly hit villages and neighboring villages that could serve as control areas. We largely limited the scope of the survey to the villages on the slopes where the landslide occurred, to have an *ex-ante* homogenous population of affected and unaffected households. Figure B1 shows each of these sites with the villages identified for our survey (the Namentsi map is shown in Figure 2 in the main text). 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 compared to clustering of dwellings in stable locations.

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 villages before the landslide event.

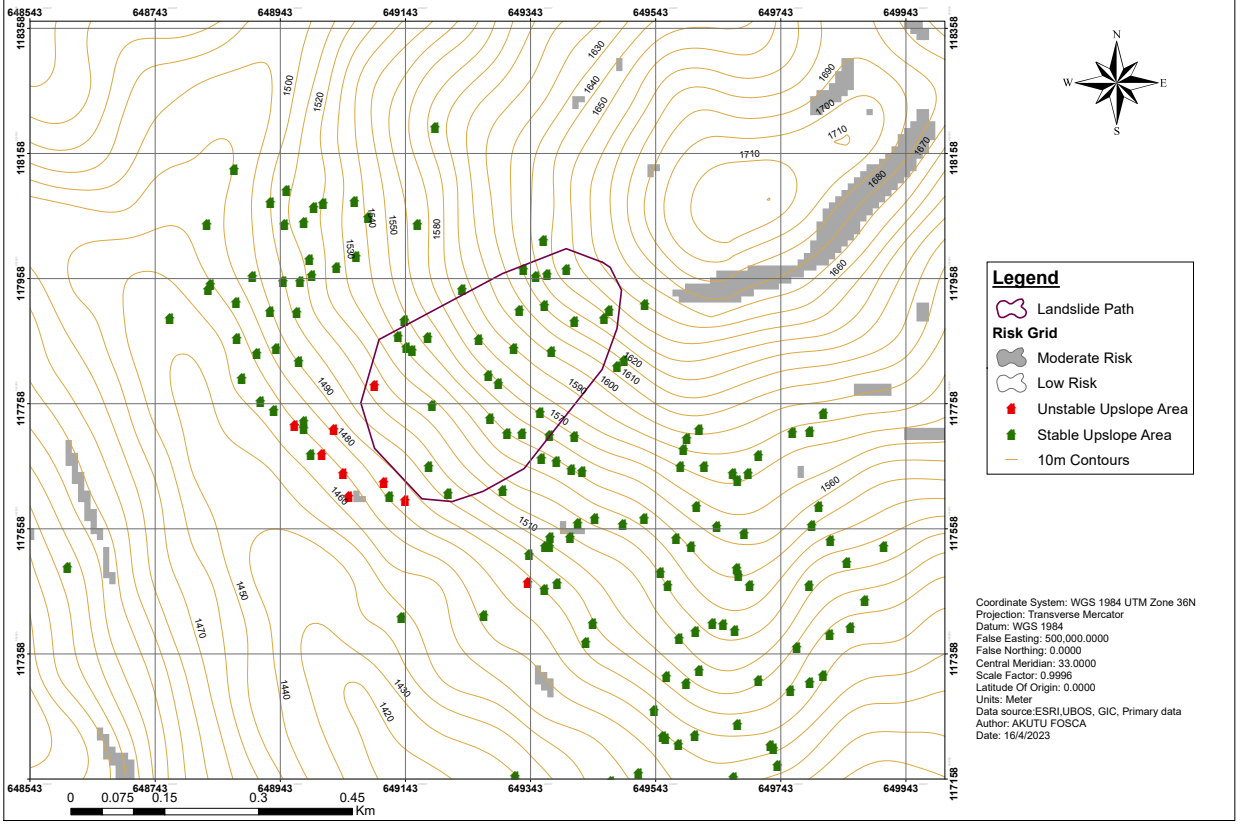
For households still living in their original dwelling, the dwelling coordinates were recorded by the survey team during interviews. For households who had moved, the coordinates at the pre-landslide location were recorded during subsequent field visits with assistance from local contacts. In cases where the original site was not safely accessible, staff were instructed to take a GPS reading as close to the original location as safely possible.

Figure B1: Additional Maps of Landslide Sites

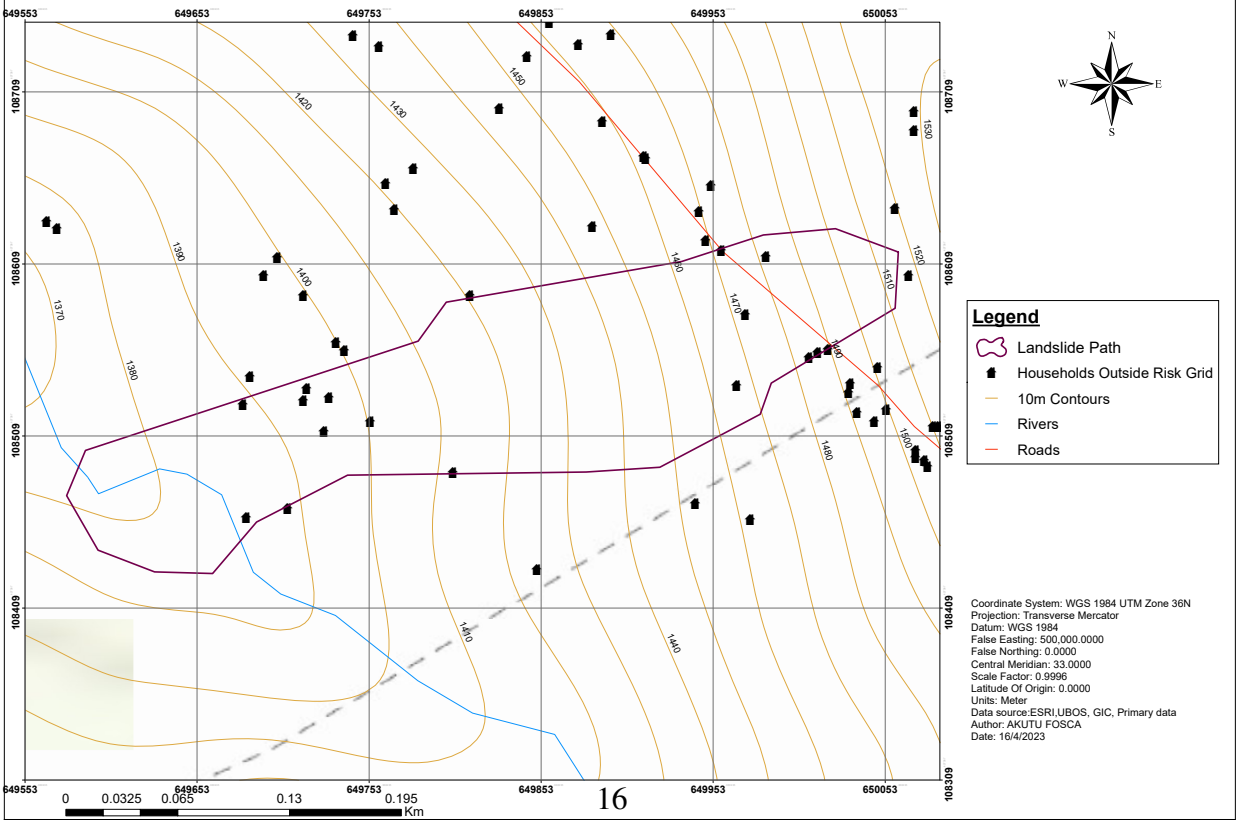


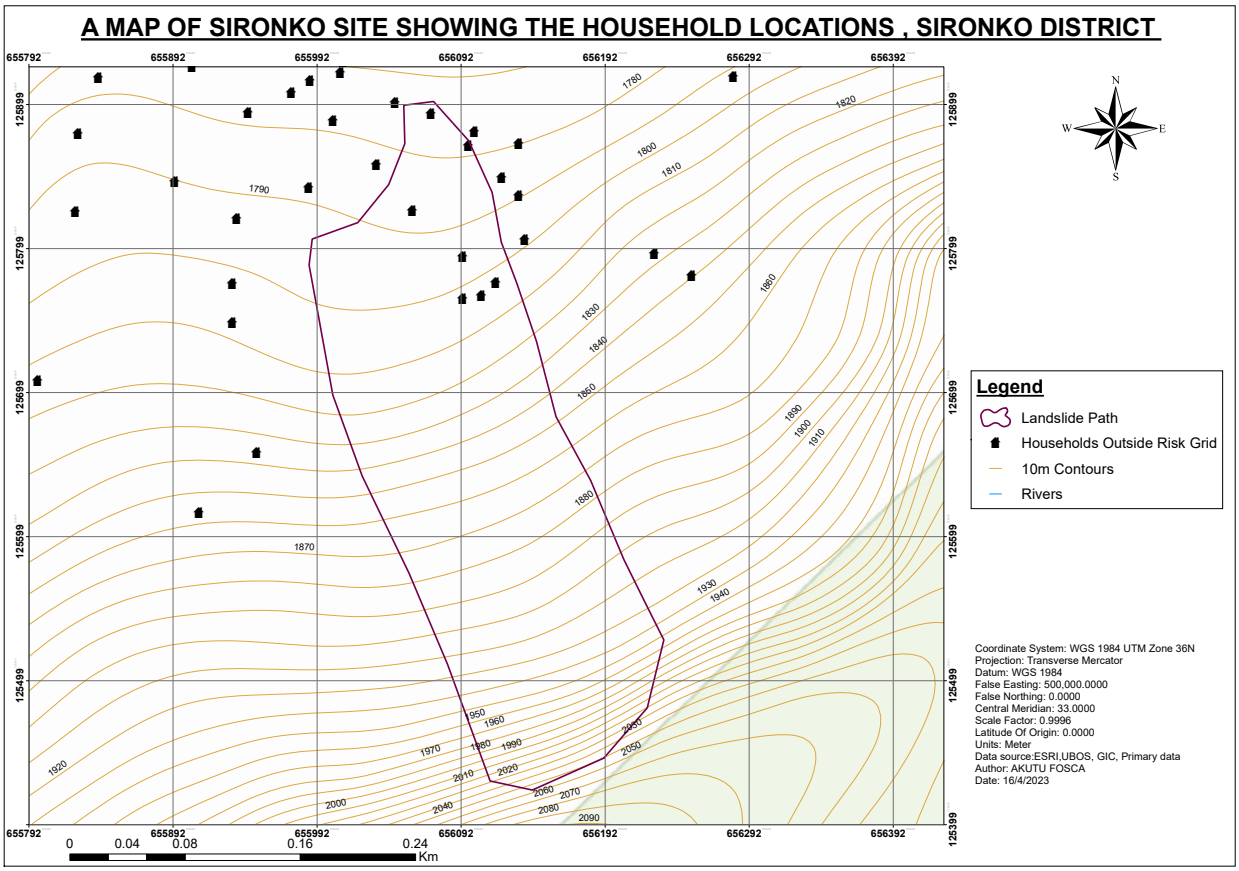


A MAP OF BUSHIKA SITE SHOWING HOUSEHOLD LOCATIONS, BUDUDA DISTRICT



A MAP OF KAATO SITE SHOWING THE HOUSEHOLD LOCATIONS , MANAFWA DISTRICT





Notes: Each house icon is a household in our sample. Green indicates that more than 75% of that household's upslope area is classified as stable; red indicates that 25% or more of the upslope area is classified as unstable. Exact landslide path shown in purple polygon.

C Corrections for Spatial Correlation

By nature, the destruction caused by landslides is spatially clustered and so may give rise to spatial correlation in regression residuals. Table C1 presents Moran tests for spatial correlation in residuals for all of our household destruction, displacement, and welfare outcomes presented in Table 2. These Moran tests suggest the presence of only modest spatial correlation: out of 14 outcomes, we reject the null hypothesis of independent and identically distributed error terms at the 10% level for three. Table C2 presents standard errors adjusted for three-dimensional spatial correlation using the method of Conley (1999), applying a cutoff of 0.01 degrees (approximately 1 kilometer). These adjusted standard errors are very similar to their unadjusted versions. Table C3 presents standard errors adjusted for three-dimension spatial correlation using the spatial correlation principal components method described in Müller and Watson (2022). Again, these adjusted standard errors are very similar to their unadjusted versions.

Table C1: Moran Tests for Spatial Correlation in Residuals

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Moran p-Value	0.49	0.43	0.01	0.39	0.59	0.18	0.00
Observations	625	625	625	625	625	625	625
Panel B: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Moran p-Value	0.47	0.88	0.20	0.64	0.10	0.41	0.44
Observations	608	606	625	625	625	625	625

Notes: An observation is a household (based on pre-landslide structure). Moran p-values estimated from regression models shown in Table 2 using Stata command *estat moran* using an inverse-distance weighting matrix with 1-kilometer truncation.

Table C2: Conley-adjusted standard errors are similar to unadjusted versions.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.332***	0.214***	0.179***	0.240***	326***	0.496***	0.246***
	(0.057)	(0.049)	(0.056)	(0.037)	(72)	(0.053)	(0.045)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.13	0.07	0.52	0.72	177	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.113***	0.113***	0.008	0.090**	0.089**	0.003	-0.075*
	(0.041)	(0.038)	(0.029)	(0.040)	(0.036)	(0.022)	(0.042)
	[0.01]	[0.00]	[0.78]	[0.02]	[0.01]	[0.89]	[0.07]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.22	0.12	0.21	0.13	0.06	0.66
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.201***	0.121**	-0.401***	-0.348***	-0.194*	-0.083	-0.373***
	(0.059)	(0.058)	(0.120)	(0.111)	(0.112)	(0.109)	(0.110)
	[0.00]	[0.04]	[0.00]	[0.00]	[0.08]	[0.45]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors and p-values adjusted for three-dimensional spatial correlation using the method of Conley (1999), estimated using the Stata package *x_ols2*, applying a cutoff of 0.01 degrees (approximately 1 kilometer). All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C3: Standard errors adjusted using Müller and Watson (2022) are similar to unadjusted versions.

Panel A: Household Destruction and Displacement	(1) House Damaged	(2) Casualty	(3) Land Damaged	(4) Any Other Damage	(5) Spending on Repairs	(6) Household Displaced	(7) Remains Displaced
Landslide	0.332***	0.214***	0.179***	0.240***	326***	0.496***	0.246**
	(0.049)	(0.032)	(0.045)	(0.042)	(71)	(0.127)	(0.100)
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.04]
Observations	625	625	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.13	0.07	0.52	0.72	177	0.18	0.03
Panel B: Individual Migration and Employment	Migrated Anywhere	Migrated to City	Migrated to Big City	Current Migrant	Remained in City	Remained in Big City	Economically Active
Landslide	0.113***	0.113**	0.008	0.090*	0.089**	0.003	-0.075
	(0.045)	(0.038)	(0.023)	(0.043)	(0.035)	(0.016)	(0.041)
	[0.04]	[0.02]	[0.76]	[0.08]	[0.04]	[0.85]	[0.12]
Observations	1,814	1,814	1,814	1,814	1,814	1,814	1,814
Dep Var Mean for Landslide = 0	0.31	0.22	0.12	0.21	0.13	0.06	0.66
Panel C: Household Welfare Measures	Satisfied With Life	Worried About Finances	Financial Health Index	Mental Health Index	Home Amenity Index	Income Index	Overall Welfare Index
Landslide	-0.201***	0.121	-0.401***	-0.348**	-0.194*	-0.083	-0.373***
	(0.049)	(0.068)	(0.120)	(0.137)	(0.091)	(0.110)	(0.064)
	[0.00]	[0.12]	[0.01]	[0.04]	[0.07]	[0.50]	[0.00]
Observations	608	606	625	625	625	625	625
Dep Var Mean for Landslide = 0	0.54	0.51	0.00	0.00	0.00	0.00	0.00

Notes: Standard errors and p-values adjusted for three-dimensional spatial correlation using the method of Müller and Watson (2022), estimated using the Stata package *scpc*. All regressions include a landslide-event fixed effect and geologic controls at the pre-landslide location. Standard errors in parentheses are heteroskedasticity-robust in Panels A and C and clustered at the household level in Panel B. Two-sided p-values in brackets. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.