Investing in land to change your risk exposure? Land transactions in a landslide prone region

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Abstract

The poor and vulnerable tend to be increasingly exposed to natural hazards like landslides. Land markets are one of the channels through which farmers get exposed to such hazards. This paper investigates the consequences of land transactions for the (un)equal distribution of exposure to landslide risk and of total land holdings in a rural area in Western Uganda. We propose and empirically test a mechanism through which land holdings and exposure to landslide risk evolves over a farmer's lifetime. A structured household survey and detailed information on land transaction as well as georeferenced information on plots was used to construct a panel dataset of land transactions. Regressions with household fixed effects were run to identify how landholdings and exposure to landslide susceptibility evolves over a farmer's lifetime. We find that farmers that are initially more exposed to landslides manage to reduce their average exposure to some extent by acquiring plots outside landslide prone areas. This goes at a cost, as farmers that are initially highly exposed acquire land more slowly than farmers that have a lower exposure on their first plot. Over a lifetime, in our case study, land transactions therefore have a somewhat levelling effect on inequality in exposure to landslide susceptibility, but increase the inequality in land ownership. As such, one of the ways through which unequal risk exposure contributes to propagating inequality in total land ownings is theoretical and empirically identified.

Key Words: Land markets, Uganda, accumulation of capital, inequality, poverty

JEL classification: Q15, D8

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1. Introduction

Much of the research in development micro-economics is concerned with poverty and growth, as well as inequality. This is particularly true for research on the efficiency and equity consequences of land transactions and on risks in agriculture. Lively debates on the consequences of land institutions have been going on for decades (Deininger et al., 2009; Place, 2009) and it is increasingly acknowledged that the poor and vulnerable tend to be strongly exposed to different types of risks, including natural risks and disasters (Collins, 2009; Kim, 2012; Wisner et al., 2003).

In general, land sales markets have been shown to have the potential to increase efficiency in agriculture, but often at some cost in equality (Deininger, 2003). The disequalizing effect of land markets has been attributed to transaction costs, the presence of distress sales and land values being inflated by their use as a collateral, as a sign of social status and as an asset for saving (Baland et al., 2007). Due to difficulties related to collecting data on plot quality, most of the studies on land transactions have considered land as an homogeneous asset, so that land endowments in these studies only differed in amount of land, rather than in quality (some noticeable exceptions are Blarel et al. (1995) and Goldstein and Udry (2008)). Land is, however, far from homogeneous, and when considering investments in land one should take into account differences in quality. The quality of a plot is determined by its potential productivity, as well as the variance in this productivity (Rao, 2014; Rosenzweig and Binswanger, 1993). When deciding to invest in agricultural land, farmers take into account both the return on investments and the risk related to this investment. Geo-recorded data now make it possible to include spatial differences in land quality when analysing land investment decisions.

In the presence of close-to-subsistence livelihoods and in the absence of insurance and well-functioning credit markets it is well-known that poor households tend to prefer low risk investments (Dercon, 2006; Rosenzweig and Binswanger, 1993). This is due to the actual, post-smoothing consumption risk being greater among poor households than among rich households (Morduch, 1995; Zimmerman and Carter, 2003). Often these low-risk investments also have low returns (Carter and Barrett, 2006; Dercon, 2006). Studies on technology adoption or on investments made by farmers and herders have shown that this tendency towards low-risk and low-return investments among poor households can lead to increasing inequality and poverty traps (Lybbert et al., 2004). To our knowledge, only one study on investment strategies among poor farmers included investments in land, and it thereby did not take into account the particularities of land as an asset (Dercon, 1998). This is deplorable, as heterogeneity in plot characteristics is frequently exploited by farmers to reduce risk (plot fragmentation is one, widely studied, example (Blarel et al., 1995; Rao, 2014)).

The (perceived) risk associated to an investment in land is not homogeneous among plots, nor among households. As plot characteristics, like slope steepness or landslide susceptibility can be observed (see further), the perceived riskiness of investment in land varies across plots. On top of that, differences in risk coping capacity and risk perceptions between farmers will make the risk associated to an investment on a certain plot to be farmer specific (Zimmerman and Carter, 2003).

In the current study on land transactions in Uganda we aim at investigating whether individual households that are participating in the land market are able to modify their exposure to landslide susceptibility. Landslides can cause serious idiosyncratic income shocks to farmers, and therefore stand as a typical example of nature induced risks which are likely to increase in frequency due to climate change (Petley, 2012). Our research exploits detailed information on past land transactions and geographical information on size and location at plot level. We find that farmers within a community manage to reduce inequalities in exposure to landslide susceptibility over time, but at the cost of an increased inequality in land holdings. We propose and test for a mechanism that explains these results, drawing on and adding to the literature on risks and inequality. Western Uganda is particularly interesting as a case study on landslides and land transactions as landslides are known to cause serious hardship in the country, while land markets are typically very active in the region (Deininger et al., 2008; Mertens et al., 2016). Our research is relevant for both literature on land markets and risks, as well as for policies that aim at reducing inequalities and exposure to natural hazards in Uganda. Contributing to the case for social justice and to the fight against poverty, this paper illustrates how inequalities can evolve in a risky environment. This is particularly relevant because climate change is likely increasing the frequency of natural hazards (UNISDR, 2015). Some policy measures that could reduce the risk provoked by exposure to landslides susceptibility are proposed.

2. Study area

We conducted our research in the Rwenzori region, in Western Uganda. This region covers an area of approximately 3000 km2 spread over 31 sub-counties in four districts: Bundibugyo, Kasese, Kabarole and Ntoroko (Figure 1). This study area is particularly relevant for our research because of frequent land transactions and the presence of a high landslide risk.

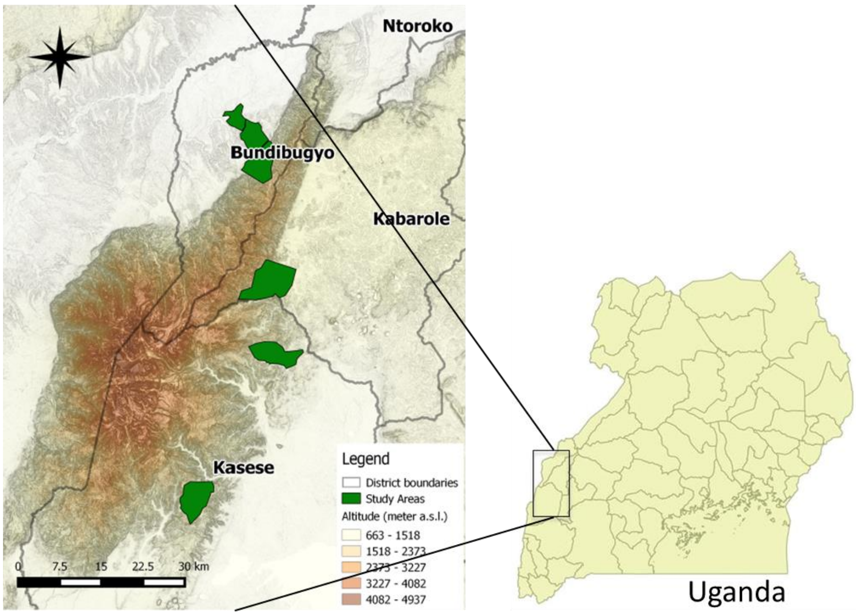

Figure 1: Overview of the study area. Darker areas have a steeper slope (adapted from Mertens et al. (2016))

2.1. Land markets in the Rwenzori region

Land sales markets in Western Uganda are very active (Deininger and Ali, 2008; Deininger and Castagnini, 2006; van Leeuwen, 2014). Farmers frequently buy and sell land, while also *inter-vivo* and *ex mortem* transfers are very common. Most of these transactions occur in a semi-formal manner, in the presence of the local chief who writes a *land agreement*, but without issuing an official titling. Despite attempts to introduce a national titling scheme , only 7% of the plots in our sample do have a land title.

The titles that are most frequently found in Western Uganda are freehold titles, which grant full private property, including the right to sell or rent the land, and customary titles, which allow land to be owned by a group of people rather than single individuals (Deininger and Ali, 2008; van Leeuwen, 2014). Two other titling schemes exist in Uganda, but are absent in Western Uganda. While official titles are virtually absent in our sample, it is widely accepted that local tenure systems, without formal titling and *de jure* enforcement, can provide sufficient tenure security for land investments (Baland et al., 1999; Katz et al., 2000; Omura, 2008).

Land sales markets in Western Uganda are active, but they are not fully ‘free’. Contrary to official regulation at national level, land in our study region is mostly owned, inherited and transacted by males only. Moreover, we noticed that there is a strong preference to keep land within ownership of members of the same ethnicity and community. Additionally, when mapping the plots owned by the households in our sample, we noted that several farmers felt tenure insecure and feared land grabbing. This is probably caused by the lack of titles and the consequential institutional multiplicity in the region (Deininger and Ali, 2008; van Leeuwen, 2014).

2.2. Landslides in the Rwenzori region

Every year, during the rainy seasons or following seismic activity landslides occur at different locations and elevations in this region (Jacobs et al., 2017). The location of these landslides is determined by the type of the soil, slope length and steepness, vegetation cover and local variations in topography (e.g. whether in a concavity or a convexity). Landslide susceptibility therefore shows a strong spatial auto-correlation (see further).

During prolonged rainfall, or during an earthquake, it frequently happens that several landslides are observed in the same village, thereby affecting multiple plots at the same time. These landslides destroy crops and productive assets such as soil fertility and therefore have a significant impact on the income of farmers in the region (Mertens et al., 2016). Reports suggest that landslides have rendered over 14,000 people homeless over the last 50 years (Jacobs et al., 2016). Landslide density in a recent field investigation has been shown to vary between 3 and 4.9 slides / km2 (Jacobs et al., 2017).

Previous studies in the region suggest that farmers are very aware of the threat caused by landslides, but that they have limited options to reduce landslide susceptibility (Mertens et al., 2017). The lack of formal insurance mechanisms compels farmers to rely on emergency measures and social networks to cope with the idiosyncratic income shock caused by landslides (Mertens et al., 2016).

3. Land transactions and risk exposure: a conceptual framework

Our conceptual framework is situated in a context of close-to-subsistence agriculture in a region with a heterogeneous landslide susceptibility and in the absence of formal insurance markets (Jacobs et al., 2017; Mertens et al., 2016). Reciprocity arrangements provide some form of insurance but this is far from complete (Mertens et al., 2016). Landslides therefore constitute an important threat. Upon occurrence of a landslide, a farmer that is close to a minimum level of consumption will first dissave non-productive assets and resort to support from social networks. Whenever this is not sufficient, the affected household will reduce consumption in an attempt to preserve its productive assets. A behaviour of smoothing productive assets, rather than consumption, has often been observed in contexts where farmer income is close to subsistence level (Carter and Lybbert, 2012; Morduch, 1995; Zimmerman and Carter, 2003).

As a serious disutility is derived from decreasing consumption below a certain level, farmers will aim at minimizing the probability of serious income losses (Wolgin, 1975; Young, 1979). What matters in this context is not only to maximize expected utility by maximizing expected income, but also and foremost to minimize the risk of a worst case scenario. This has been termed disaster avoidance behaviour (Chavas, 2004; Rosenzweig and Binswanger, 1993).

In most parts of our study area options to diversify income strategies outside agriculture are rather limited. Households therefore have to rely on asset-based prevention and coping mechanisms against the risk of falling below a minimum level of consumption due to landslides. The most important productive asset is land, both historically and at present. Risk diversification is possible by scattering plots in order to reduce the probability of having all plots affected by the same landslide, or by making use of the heterogeneity of landslide susceptibility in the region and making sure to have at least one plot that is not susceptible to landslides . The latter option is particularly relevant as both a temporal and spatial auto-correlation exists in landslide occurrence: simultaneous occurrence of landslides on several plots in the same village can pose a serious income threat, even to farmers that have a strong network of informal insurance. Additionally, the spatial auto-correlation in landslide susceptibility increases the likelihood that scattered plots which are not sufficiently[2] far from each other have a similar susceptibility and might therefore be hit by a landslide during the same rainy season.

A positive utility is therefore derived from having or cultivating at least one plot that is not exposed to landslide susceptibility. As such, we hypothesise that farmers that are initially endowed with plots with a high landslide susceptibility will tend to acquire plots with a lower landslide susceptibility in order to reduce their risk exposure (**Proposition 1)**. This is not straightforward, as the susceptibility of plots is geographically clustered, meaning that households need to do a substantial effort to find and cultivate land that has a different level of landslide susceptibility. Moreover, plots with a low landslide susceptibility might be more expensive. As a part of the farmer population (the exposed farmers) has a strong preference for safe land, the price of land that is not prone to landslides might increase relatively to land that is not landslide prone.

A farmer that is very exposed to landslide susceptibility, and thus faces a high threat of falling below a certain consumption level, might be willing to pay a higher risk premium for a safe plot than a farmer that is quite confident about its income. Conversely, households that have land in safe zones will not be willing to pay a risk premium for land with a low exposure and will therefore buy the cheaper plots that have a relatively higher exposure. This leads us to hypothesise that everything else being equal, farmers that are initially endowed with plots in

[2] See further (Figure 2) for an actual explanation of what is meant with 'sufficiently far'.

safe areas will, on average, tend to acquire plots in more susceptible areas in order to increase their land holdings (**Proposition 2)**.

The combination of propositions 1 and 2 leads us to the hypothesis that inequality in exposure between farmers at the same stage of their career will decrease over the lifetime of these farmers. Yet this might go at the expense of an increasing inequality in land holdings, whereby those that are initially least exposed are able to acquire more land (**Proposition 3)**.

Of course, what is considered as an acceptable exposure to landslide risk is individual-specific and depends on what a person has experienced and observed in his/her lifetime (Cameron and Shah, 2015; Olbrich et al., 2012). Also what is considered a minimum consumption level differs between farmers and is determined by experiences and observations. While withdrawing children from school after a landslide might be acceptable for some, it is an unacceptable idea for others. Studies have shown that people anchor their perceptions and beliefs on previous experiences and observations of their surroundings (Loewenstein and Angner, 2003; Olbrich et al., 2012).

This conceptual framework is closely related to the research of Zimmerman and Carter (2003), in which poor farmers pursue an asset smoothing path to reduce risks, but at a significant cost. Our conceptual framework differs from their model in the sense that no initial difference in income or in the quantity of asset holding is required in order to observe different asset accumulation paths. In our framework the difference in exposure to potentially disastrous income shocks, between equally endowed households, is sufficient to motivate diverging patterns of asset accumulation. As such, the main addition of our analysis is to explicitly pin down one of the reasons, i.e. risk exposure, behind the different income pathways followed by poor and wealthy farmers.

Our conceptual framework does not explicitly consider risk preferences as an explanatory driver for differences in land acquisition strategies. Yet, it is to be expected that observed differences in risk exposure are also reflecting differing risk preferences (Gloede et al., 2015). We therefore also investigate how risk preferences, risk aversion, under- and overestimation of small probabilities and loss aversion, vary across different levels of exposure (Kahneman and Tversky, 1979).

4. Data collection

4.1. The sample

We surveyed a stratified two-stage random sample of 401 households (HHs) in 41 remote villages in the Rwenzori region (Figure 1). Crop cultivation is the most important source of income in the region. In our sample, 68% of the plots are being planted with coffee or cocoa and average income per adult equivalent is below one dollar a day (Mertens et al., 2016).

Villages and HHs affected by landslides were identified prior to the survey implementation, respectively through workshops and field visits at district level, as well as village-level interviews with local chair persons (see Mertens et al., 2016). The villages were subsequently stratified on the presence of recent landslides, and the HHs in each village were stratified on whether they had been affected by a landslide in the previous 15 years. Households that have experienced landslides have been oversampled.

The HHs in our sample were visited for a first time with paper questionnaires in February-March 2015, during which most questions were asked, and a second time with questionnaires on tablets[3] in August-September 2016. During the second visit a game was played to elicit risk preferences and additional plots were mapped. Only HHs that were interviewed in both rounds are included in this analysis. Attrition is very low (3%). Four HHs were dropped during data cleaning, because the HH head refused to answer questions on plot cultivation and ownership. Our final sample therefore contains 397 HHs. An overview of the sample characteristics is given in Table 1.

The questionnaire included questions on household demographics, perceptions and experience with landslides, detailed information on plot ownership, plot transactions and plot cultivation, as well as questions on agricultural production and all questions needed to determine household income (The World Bank, 2000). Plots are defined as continuous pieces of land that were obtained during a same land transaction. If two adjacent pieces of land were obtained at different moments in time, we therefore consider them as different plots. As we do only have information about the year of plot acquisition, adjacent plots that were acquired during different transactions in the same year could not be differentiated and are grouped in the analysis.

GPS points were taken in front of the farm houses and on the corners of each plot owned or cultivated by the HHs. Some plots could not be mapped due to refusal by the owner to bring the enumerators to their plots. This was most frequently related to an excessive walking distance from the house to the plot. Other plots could not be mapped because the boundaries were contested by neighbours, because technical errors were made during mapping, or because the plots were rented in and the agreement was needed from the owner. Also plots that had been under ownership in the past but weren't anymore at the time of the survey could not be mapped.

[3] Tablets were used in the second time to increase efficiency and to allow a true randomization of the questions in the risk game. Survey CTO was used on Samsung tablets.

In total 784 plots, or 75 % of the 1040 plots owned and cultivated by the households in our sample[4], were mapped with a GPS.

4.2. Geographic information at plot level

The georeferencing of the plots was used to extract information about their size, landslide susceptibility, slope steepness, as well as distance from the house and from the road network. The use of GPS devices to georeference plots has been praised for being a cheap and accurate technique of obtaining detailed geographical information about plots (Carletto et al., 2016).

The probability to have a landslide on a plot is determined by the probability that a landslide starts on the plot or in the close surroundings of the plot and thereby leads to a withdrawal or a deposition of soil respectively from or on the plot. This probability was therefore calculated by estimating the landslide susceptibility in a buffer of 30 meters around the plot[5]. The susceptibility data were obtained from a regional landslide susceptibility map produced through logistic regression modelling at 30m resolution. The main variables taken into account for this susceptibility assessment were lithology, average annual precipitation and topographic variables such as slope gradient, curvature, topographic wetness and aspect. Field inventories were used to calibrate and validate the model (Jacobs et al., 2017b).

A strong spatial correlation in susceptibility exists within the region. Figure 2 illustrates how the correlation in susceptibility of two plots evolves with increasing distance between these plots, as measured by the Moran I statistic (which was calculated with the statistical package R). At a distance of 550 meters correlation in susceptibility is still as high as 0.5, while a distance of approximately 2 km is needed to have a correlation below 0.2.

[4] 78 plots were owned but not cultivated by the household at the time of the surveys, either because the plots were under fallow or because they were rented out. Only 19 of these plots were actually mapped. They are not included in the analysis, but including them does not change the results. 56 plots were being rented in, but are also not included in the analysis.

[5] The sensitivity of our results to buffer size was tested by running the same analysis with a buffer of 15 meters around the plot.

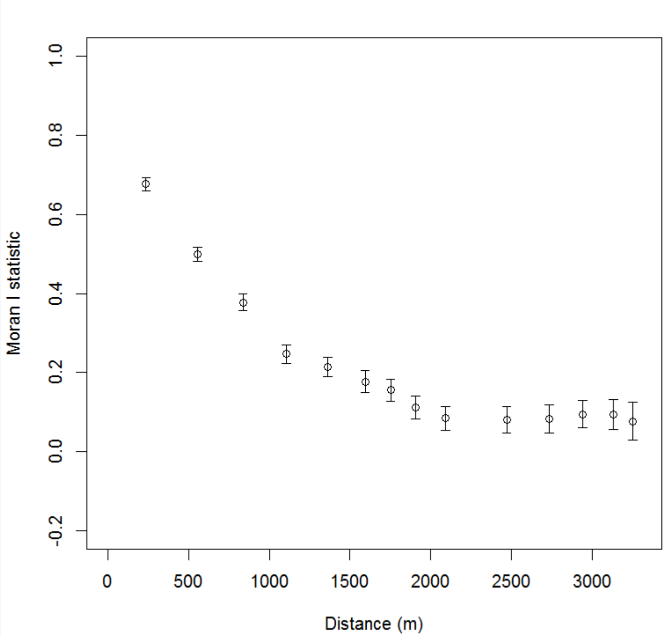

Figure 2: Spatial correlation (Moran I) in susceptibility between all measured plots at different distances (in meters). Correlation reaches 0 near 5000 meters distance only. At a distance of 250m, correlation is 0.68, while it is 0.5 at a distance of 550 m.

After extracting landslide susceptibility estimates for all plots, the data were normalized over the whole sample. Total exposure to landslide susceptibility at HH level at any point in time was estimated by taking the average susceptibility, weighted by plot size, from those plots that have been mapped. A similar procedure has been followed to estimate slope gradient at plot and HH level at any point in time.

Plot sizes were also obtained from the mapped plots. For those plots that have not been mapped, plot size was estimated by imputation from the plot areas reported by the farmers. For those households for whom more than one plot was mapped, the average ratio between stated and mapped plot sizes was estimated. This ratio was then used to correct stated plot sizes of non-mapped plots. Among those households for whom only one plot was mapped, sample-average ratios between stated and mapped plots were used. This approach is very similar to the imputation method proposed and tested by the Wold Bank (Kilic et al., 2013). As such, information on landslide susceptibility, slope and plot location is only available for those plots that were mapped, while information on the (estimated) size of the plots is available for all plots.

4.3. Obtaining risk preferences

Risk preferences were elicited through a lab in the field experiment with real monetary pay-offs, as described in Tanaka et al. (2016). At the beginning of the interview in 2016 a monetary compensation of 3000 Ush (0.83 USD) was promised because the questionnaire was long and the mapping of the plots required some time and effort from the respondents. This is the equivalent of 93 % of the average income per day per adult equivalent in our sample. At the end of the interview, the respondents were asked whether they would be willing to play a risk game. The expected value of this game was 5557 Ush (1.54 USD), making the total expected compensation for the interview 8557 Ush. Yet, as the risk game entailed a small chance of losses, a risk taking respondent with very bad luck would earn only 1215 Ush. Great emphasis was put on the fact that this would entail a loss of already earned money (i.e. 1215 Ush. instead of 3000 Ush.) rather than just a foregone income. As the money was not really given to the farmers before the start of the game, we do not know whether this was sufficient to ascertain that loss aversion was being measured. The rules of the game were made clear to the respondent before the start of the game and the risk game was only played with informed consent. A farmer refusing to play the risk game would just receive the 3000 Ush. Only 3 farmers refused to play the game, for religious reasons.

The risk game method consisted of presenting 35 choice sets with binary lotteries that involve gains and losses with different probabilities (Tanaka et al., 2016). After every interview, one of these choice sets was randomly selected to be played for real monetary pay-off. The advantage of this method is that it allows to identify risk aversion, loss aversion and overweighting or underweighting of small probabilities, as predicted by prospect theory (Kahneman and Tversky, 1979). Risk aversion (σ) measures the extent to which uncertainty decreases the utility of expected gains, while loss aversion (λ) does the same for expected losses. The curvature of the probability weighting function (α) is a measure for overweighting or underweighting small probabilities. Most people tend to overweight small probabilities (Kahneman and Tversky, 1979).

5. Empirical model

5.1. Baseline regressions

Regressions with household fixed effects are used to investigate how exposure and land holdings evolve over time. We make use of information about the first plot that was acquired and cultivated by the household, at the time that the household head started his/her own farm. A distinction is made between farmers with more or less exposure to landslide susceptibility on their first plot as well as between farmers with smaller or larger first plots. The following equation is therefore fitted on the data:

$$Y_{it} = \alpha + \beta_1 Time_{it} + \beta_2 InEx_i * Time_{it} + \beta_3 InLo_i * Time_{it} + HHFE_i + \varepsilon_{it} \qquad \text{Eq. 1}$$

In this equation Y_{it} stands for either the average exposure at HH level or the total land holdings of household i after transaction t. $InEx_i$ is a measure for the initial exposure of household i, while $InLo_i$ represents the initial land ownership of household i. In the main regressions (Table

3), $InEx_i$ is a dummy, which equals 1 if the landslide susceptibility is above the sub-county median, and zero if equal or below, while $InLo_i$ is a dummy, which equals 1 if the initial area owned is above the sub-county median, and zero if equal or below. A threshold at Sub-County level was chosen because individuals base their choices on the experiences and observations of their surroundings. A farmer's preference is determined by what s/he learned to consider as a normal level of exposure by observing neighbours and discussing with friends. The median was chosen because it represents this best. This being said, other thresholds like the mean at Sub-County level or the median or mean at the level of the whole sample give similar results. During robustness checks also a continuous measure of initial exposure and initial endowment was tested (Table 4).

The households in our sample do not all have the same age, nor do they have the same experience with farming. We do therefore not compare their current land holdings, but look at how these land holdings evolved over time, everything else being equal. Therefore, $Time_{it}$ is our source of orthogonal variation, being the number of years since the acquisition of the first plot at the moment of the transaction[6]. $HHFE_i$ are household fixed effects. Household fixed effects are used to control for the diverse household-specific factors that determine the acquisition of land. As such, the estimation of Eq. 1 also controls for differences between HHs in risk preferences and in past experiences with landslides. To make sure that the results are not dominated by households owning a large number of plots, standard errors are clustered and weights for the number of plots (i.e. observations) per household are included.

The regression specified in Eq. 1 does not directly estimate the relation between the initial situation and subsequent exposure and landholdings, but instead looks at how the effect of time differs depending on the initial situation[7]. Balance tests that compare characteristics of both groups with t-tests are used and illustrate that farmers with different initial exposure are relatively similar at the start (see appendix). Similar balance tests are used to compare farmers that have different initial total land ownings (see appendix).

The regression in Eq. 1 can be used to investigate how either exposure to landslide susceptibility or land holdings evolve over time, depending on the initial susceptibility on the first plot. To test the propositions in the conceptual framework it would be necessary to show that this

[6] Alternatively, age of the household head could be used. As we use household fixed effects, this produces the same results (with a different intercept).

[7] One should note that we do not have information on size or susceptibility of plots that were sold or given away, so that our variables of exposure and land ownings are only based on plots that are currently owned. 15% of the households reports to have sold or given away a plot. Dropping these households from the analysis does not change the results.

process is, at least partially, driven by actual purposeful choices made by the households in our sample. In case landslide susceptibility was randomly distributed on plots, without any spatial correlation, convergence in exposure between the two groups in our sample would naturally occur during plot acquisition. As such, households that were initially exposed would, on average, reduce their exposure by acquiring plots without caring about their susceptibility. In the presence of a strong correlation in susceptibility across nearby plots, changing ones' initial exposure is not self-evident anymore. Households have to target plots with a specific landslide susceptibility, sometimes at the cost of a longer distance between plots.

Therefore, we investigate whether the trend that is observed in our sample is more than a random process in a given context of autocorrelation. Our regressions results are compared with the results that one would expect if the susceptibility of the newly acquired plot was the outcome of a truly random process in the presence of special auto-correlation. We therefore did a Monte-Carlo simulation with 500 draws whereby landslide susceptibility was predicted on all non-first plots in our sample. We made use of a standard normal distribution with a correlation of 0.5 with the susceptibility on the first plot. This represents a situation in which farmers would randomly acquire their plots in an environment with spatial correlation. A correlation of 0.5 was chosen because it corresponds to the correlation one observes at a distance of 530 meters (Figure 2), which is the average distance between plots in our sample[8] (Table 1). The change in exposure is expected to be larger and more significant if it is the outcome of purposeful choices by the farmers than if the process is fully random with regard to landslide susceptibility.

5.2. Robustness tests

To investigate how risk preferences might be related to our results, equation 2 was also tested (Table 5).

$$Y_{it} = \alpha + \beta_1 Time_{it} + \beta_2 InEx_i * Time_{it} + \beta_3 InLo_i * Time_{it} + \beta_4 Risk_i * Time_{it} + HHFE_i + \varepsilon_{it} \qquad \text{Eq. 2}$$

In this equation, the three variables that measure the risk preferences of the household head are interacted with time ($Risk_i * Time_{it}$), so as to investigate whether different evolutions in exposure and in land ownership vary with the risk preferences of the household head. Other variables in this equation are the same as in equation 1. One should note that we measured risk preference at the time of the survey, not at the moment of the land transactions.

The estimation of equation 1 and 2 does not take into account plot characteristics other than landslide susceptibility. We therefore tested a specification which included control variables

[8] This is a rather conservative choice, as the median distance between plots in our sample is 350 m.

like slope steepness, the distance from the house, plot size or a dummy for whether the plot was purchased. We do not have measures for soil quality or for the presence of plot improvements before the acquisition of the plot. The results of this analysis are presented in the Table 5.

One could argue that it is not the initial exposure which determines whether a farmer will acquire a plot with a high or a low susceptibility, but rather his/her exposure at the time of the decision, so just before acquisition. Therefore, an alternative way to test proposition 1 and 2 formulated in the conceptual framework would be to estimate the following equation:

$$Y_{it} = \alpha + \beta Y_{it-1} + \gamma Area_{it-1} + \mu HHFE_i + \varepsilon_{it} \qquad \text{Eq. 3}$$

Here Y_{it} stands for the average exposure of household i after transaction t. Y_{it-1} and $Area_{it-1}$ respectively represent exposure and the total land ownings of household i after transaction t-1[9]. While the estimation of Eq. 3 is relevant for answering our research questions, it suffers from three problems. First, equation 3 cannot test proposition 3, as it does not look at the long term consequences of initial unequal exposure for land holdings. Second, it can only run for households that have at least three plots for which we have both geographic information and reliable information on the order of acquisition. Third, a problem of autocorrelation may arise, since the susceptibility at a certain moment depends on the susceptibility of the plots acquired in previous time steps. Nevertheless, the results of estimations with Eq. 3 are presented as a robustness check, together with the results of a Wooldridge autocorrelation test (Table 6). We expect the problem of autocorrelation might not be pressing since the number of time steps is limited.

6. Descriptive statistics

On average the farmers in our sample started off their career with a land holding of 0.46 ha at the age of 24 and managed to increase this acreage up till 1.21 ha by the age of 47, the average age of the household head at the time of the survey (Table 1). This is more than a twofold increase in twenty years. The farmers did so by acquiring new plots, through purchases, inheritance or other transfers. By acquiring these plots they managed to increase their land holding and to change their exposure to landslide susceptibility.

In Table 1 we therefore divided the whole sample in three groups. A first group consists of those farmers that did not acquire more than one plot or for whom we do not know how

[9] Instead of average exposure to landslide susceptibility at t-1 as an explanatory variable, the same equation could be estimated with landslide susceptibility on the least exposed plot at t-1. Following the idea of disaster avoidance, we would expect a negative correlation between susceptibility on the least exposed plot and susceptibility on the newly acquired plots: as long as the plot that is least susceptible is sufficiently large and safe to limit the risk of falling below a level of minimum consumption, more risky plots can be acquired. Our results (not shown) confirm this hypothesis.

exposure has changed over time. The second group consists of those farmers for whom the average exposure to landslides susceptibility increased over time, while the third one consists of those that decreased in exposure over their lifetime.

Group 1 includes households that have only one plot (30%), those that sold their first plot (6%), that have several plots but all acquired in the same year (12%) or they are the households for whom we did not manage to map the first plot (20%) or none of their subsequent plots (32%). The households in this group differ from the rest of our sample in that they have less HH members, own a smaller number of plots, but not a smaller area and have a lower exposure to landslide susceptibility on the mapped plots. As it was not possible to identify a change in exposure for the households in this group, they will not be used in the further analysis on exposure to landslide susceptibility. Excluding these households from our analysis implies that the observations made in this research only hold for farmers that do participate in the land market and that did still own their first plot at the time of the survey.

The two other groups (Table 1) together own a total of 657 plots and do not differ in most household characteristics, except for initial and final exposure to landslide. Unsurprisingly, farmers that increased in exposure to landslide susceptibility in the course of their lifetime started with a plot that had a significantly lower susceptibility than those that decreased in exposure. More surprising, though, is that the former farmers were on average more exposed to landslide susceptibility than the latter at the time of the survey. This is not straightforward, as landslide susceptibility is geographically clustered and the acquisition of plots with a different susceptibility typically comes with larger search costs, travel costs and increased monitoring costs. On average, households that increased in exposure own slightly more plots, but not more area of land, at the time of the survey than those that decreased.

It is worth having a look at the three variables that measure the risk preferences of the households. While none of the measures (risk aversion σ, shape of the value function α, loss aversion λ) is significantly different between the groups at the 10% level, a significant difference exists at the 11% level in α between those farmers that increased their susceptibility and those that decreased it. This implies that there is some indication of larger overweighting of small probabilities among those farmers that decreased their exposure to landslide susceptibility over time.

Table I: Means and standard deviations (sd) of household characteristics for the whole sample, as well as for three subgroups. The first group consists of farmers for whom we could not observe a change in exposure to landslide susceptibility over time, while group 2 are farmers that increased in exposure and group 3 are those that decreased. The result of T-tests on differences between groups are given between the columns (p < 0.10, ** p < 0.05, *** p < 0.01).*

	All	Group 1 No change in	Group 2 Susceptibility	Group 3 Susceptibility

			susceptibility observed	increased		decreased
Household characteristics at the time of the survey						
Age household (HH) head	46.56 (15.39)		47.45 (16.70)	44.39 (14.45)		47.14 (13.96)
Years of formal education HH head	5.77 (4.04)		5.61 (4.35)	6.18 (3.88)		5.63 (3.67)
Adult equivalents (OECD scales)	3.50 (1.19)	***	3.32 (1.14)	3.56 (1.11)		3.72 (1.29)
Log(Income) [Ush/adult equivalent/day]	7.60 (1.05)	***	7.39 (1.09)	7.70 (1.00)		7.84 (0.99)
% of income from agriculture	86.06 (22.83)		86.49 (23.48)	87.02 (21.71)		84.51 (22.91)
Total area owned [Ha]	1.21 (1.25)		1.22 (1.49)	1.28 (1.15)		1.11 (0.89)
Number of plots owned	3.05 (1.94)	***	2.63 (2.20)	3.62 (1.89)	*	3.20 (1.32)
Number of plots purchased	1.54 (1.73)	***	1.16 (1.80)	1.98 (1.82)		1.73 (1.40)
Number of plots ever sold or given away	0.22 (0.66)		0.21 (0.61)	0.29 (0.90)		0.18 (0.45)
Average distance between plots [m]	536 (650)		582 (747)	510 (638)		536 (611)
Average exposure to landslide susceptibility at the time of the survey [min: -2.3; med: 0.15; max: 1.8]	-0.14 (0.90)	***	-0.32 (0.93)	0.10 (0.78)	*	-0.09 (0.91)
σ (risk aversion) Higher value = more risk averse [min: 0.1; med: 0.7; max: 1.5]	0.89 (0.53)		0.88 (0.53)	0.87 (0.50)		0.92 (0.55)
α (shape of the probability weighting function) α < 1 : overweighting small probabilities [min: 0.1; med: 0.8; max: 1.5]	0.82 (0.37)		0.81 (0.36)	0.88 (0.39)		0.79 (0.36)
λ (loss aversion) λ > 1 : loss averse[#] [min: 0.1; med: 1.75; max: 10]	2.66 (3.07)		2.84 (3.23)	2.77 (3.17)		2.29 (2.72)
Characteristics first plot						
LS susceptibility on first plot [min: -2.23; med: 0.00; max: 1.77]	-0.09 (0.96)	**	-0.24 (0.95)	-0.26 (0.92)	***	0.23 (0.96)
Susceptibility first plot is above SubCounty median [1 if yes] [min: -2.2; med: 0.17; max: 1.8]	0.48 (0.50)		0.48 (0.50)	0.29 (0.46)	***	0.65 (0.48)
Size first plot [Ha]	0.46 (0.51)	***	0.53 (0.62)	0.41 (0.41)		0.38 (0.36)
Area first plot is above Sub-County median [1 if yes]	0.13 (0.33)		0.14 (0.35)	0.12 (0.32)		0.11 (0.32)
Age HHH when acquired first plot	24.28 (12.18)	***	26.31 (13.87)	21.89 (9.90)		23.29 (10.75)
First plot purchased [1 if yes]	0.32 (0.47)		0.29 (0.46)	0.32 (0.47)		0.37 (0.48)
Sample characteristics						
Percentage of plots that are	0.19	***	0.27	0.12		0.11

not mapped	(0.26)	(0.30)	(0.20)	(0.19)
Observations (# HHs)	397	179	104	114

Due to a programming mistake on the tablets some lotteries on loss aversion were randomly not asked to some random households in our sample (approx. 2/3 of the sample missed one question at least), only allowing us to get approximate values for loss aversion for these farmers.

It is obvious that changes in exposure to landslide susceptibility over time are to a great extent determined by individual decisions. As these decisions can be determined by a plethora of different factors, an analysis that would compare households based on the change in susceptibility ex post would be highly endogenous. The results in Table 1 are therefore indicative, but they suggest that one of the main factors correlated with the decision to acquire land in susceptible area is the susceptibility on the first plot.

The majority of the first plots is inherited through *in vivo* or *ex mortem* transfers from parents to their son. While within-household bargaining processes, birth-rank, and gender as an extreme example, do determine the distribution of the plots, the land one inherits is necessarily constrained by plot portfolio available to the parents as well as some likely equity concerns (among males at least). In the subsequent steps of the analysis the sample has therefore been split, not based on the direction of the change in exposure, but on whether the susceptibility of the first plot was above or below the median of the susceptibility in the Sub-County. Balance tests comparing the households in these groups suggest a strong similarity between households with initial exposure above or below Sub-County median. The table with balance tests is very similar to Table 1 and has therefore been presented in the Appendix.

Table 2 illustrates some differences between first plots and later plots for the whole sample and differentiated between farmers for whom susceptibility on the first plot was above or below Sub-County median. While on average there is no difference in susceptibility on the first plot and on later plots for the whole sample, a clear difference appears when the sample is split between households with a high initial exposure and households with a low initial exposure (Table 2). One should note that the gap in susceptibility between both groups is smaller for non-first plots than for first plots, but does not totally disappear. We find that farmers that started with a plot that had a high landslide susceptibility tend to acquire smaller plots than those that started with a plot with a low landslide susceptibility.

Table II: Means and standard deviation (sd) for characteristics at plot level for all plots (column 1), first plots only (column 2) and plots acquired at a later stage (column 3). The result of T-tests on differences between groups are given between column 2 and 3 (p < 0.10, ** p < 0.05, *** p < 0.01). Different lines show these results for respectively the whole sample (first line), households (HH) with the susceptibility on the first plot above Sub-County median (second line) and those with the susceptibility on the first plot below Sub-County median (third line).*

	All plots	First plot	Not first plot
Landslide Susceptibility			
Whole sample	0.01	-0.04	0.07
	(0.99)	(0.97)	(1.01)

HH with susceptibility on first plot below S/C median	-0.35	-0.63	***	-0.13
	(0.99)	(0.86)		(1.04)
HH with susceptibility on first plot above S/C median	0.43	0.51	**	0.33
	(0.81)	(0.71)		(0.90)
Plot size (Ha)				
Whole sample	0.40	0.45	***	0.37
	(0.50)	(0.51)		(0.49)
HH with susceptibility on first plot below S/C median	0.42	0.46		0.39
	(0.57)	(0.58)		(0.57)
HH with susceptibility on first plot above S/C median	0.39	0.44	***	0.34
	(0.37)	(0.41)		(0.32)
Purchased (= 1 if plot was purchased)				
Whole sample	0.53	0.33	***	0.67
	(0.50)	(0.47)		(0.47)
HH with susceptibility on first plot below S/C median	0.56	0.32	***	0.70
	(0.50)	(0.47)		(0.46)
HH with susceptibility on first plot above S/C median	0.49	0.34	***	0.61
	(0.50)	(0.47)		(0.49)
Distance from the house [m]				
Whole sample	337	287	***	382
	(534)	(609)		(451)
HH with susceptibility on first plot below S/C median	283	206	***	342
	(484)	(539)		(429)
HH with susceptibility on first plot above S/C median	398	364		436
	(587)	(672)		(478)
Slope steepness [degree]				
Whole sample	14.14	14.91	**	13.45
[min: 1.7; med: 12.6; max: 35.8]	(7.95)	(7.71)		(8.10)
HH with susceptibility on first plot below S/C median	12.16	11.75		12.47
	(7.19)	(6.19)		(7.86)
HH with susceptibility on first plot above S/C median	16.42	17.91	***	14.78
	(8.17)	(7.83)		(8.24)
Observations				
Whole sample	1040	424		616
Plots of HH with susceptibility on first plot below S/C median	602	224		378
Plots of HH with susceptibility on first plot above S/C median	438	200		238

7. Results

7.1. Regressions with household fixed effects

Column A of Table 3 shows how average exposure of a household to landslides susceptibility changes with time. The coefficient indicates the direction and average speed or magnitude of change in exposure per year. On average, exposure to landslide susceptibility increases with time, except for farmers that start with a more-than-median exposure. Exposure to landslides susceptibility among these farmers actually decreases with time. The effect on the inequality in exposure is important, as in the course of 30 years the gap between farmers that were initially exposed and those that were not decreases by half a standard deviation. Farmers do not manage to fully bridge the gap in exposure, as the initial difference in susceptibility on the first plot of exposed and non-exposed households was more than one standard deviation (see Appendix). When comparing these results (column A) with the results of the simulation (column B in Table 3), it becomes clear that farmers do actually target plots with a specific level of susceptibility, depending on their initial exposure[10]. Despite the strong spatial correlation in susceptibility, the difference in average level of exposure reduces to an extent which is stronger than what would be expected if it had been a random process in the presence of spatial auto-correlation[11]. One should note that a correlation of 0.5 was chosen for the simulation of the results in column B (Table 3). This equals the observed spatial correlation at the average distance between plots and this is lower than the spatial correlation at median distance between plots. Also, the observed distance between plots in our sample is the result of actual choices made by the households, probably driven by a desire to scatter plots. The gap between the coefficients in column A and column B of Table 3 is therefore probably a conservative estimation.

Column C of Table 3 illustrates how land holdings have evolved over time, differentiated according to initial exposure and initial land holdings. The first coefficient indicates that, over 30 years, farmers increased their holdings by 1 ha on average. Yet for farmers that started with a plot that was exposed to landslides the increase in landholdings is more than half that speed, while for farmers that started off with a larger amount of land, this increase is faster. This suggests that the initially exposed accumulate land slower than average, while the farmers that start with more land accumulate land faster. As an additional illustration, the evolution in land holdings over time has been mapped in Figure A1 in the appendix.

Together, the findings from Table 3 suggest that inequality in landslide exposure between farmers with the same experience decreases, but that inequality increases in land holdings over time. As such, farmers or communities trade off inequality in exposure for inequality in total land area.

Table III: regression results of equation 1 with real data (column A and C) and simulated data (column B). Household fixed effects and sampling weights are used. T-statistics are in parentheses (p < 0.10, ** p < 0.05, *** p < 0.01).*

	Column A Average **susceptibility** of land ownings after this plot was acquired	Column B Simulated average susceptibility if acquisition was random and spatial correlation of 0.5 in susceptibility	Column C Total **area** of land owning after this plot was acquired
Years since first plot	0.011***	0.005***	0.033***
	(3.34)	(2.62)	(4.91)
Years since first plot * Susceptibility first plot above S/C median	-0.017***	-0.010***	-0.017**
	(-4.78)	(-5.11)	(-2.24)
Years since first plot *	-0.004	-0.001	0.015**

[10] No formal test can compare coefficients of different regressions that do not have the same dependent variable. Yet, individual tests on the coefficients can give an idea. At the 5 % confidence level the coefficient β_1 of column A is still significantly larger than 0.057, while it is only larger than 0.020 in column B. The coefficient β_2 of column A is still significantly smaller than -0.010 at the 5% level, while it is only smaller than 0.07 in column B.

[11] And close to what would have been the case if there was no spatial auto-correlation (not shown).

Size first plot above S/C median	(-1.03)	(-0.67)	(2.38)
Constant	-0.117**	-0.091***	-0.233**
	(-2.38)	(-3.25)	(-2.14)
N	708	708	874
Within model R^2 (r2_w)	0.06	0.12	0.31
F statistic	7.66	10.40	29.30
p-value (F statistic)	0.00	0.00	0.00

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7.2. Robustness of main results

In this section we investigate the robustness of our main results. First the robustness of the results is tested against different specifications. Then various explanations and interpretations of these results are put forward and tested

Alternative threshold and continuous interaction term

While the results in Table 3 suggests that the distinction between farmers that increase their exposure over time and farmers that decrease it coincides with the difference in initial susceptibility, the choice for a threshold above or below Sub-County median might seem arbitrary. A similar concern applies for the threshold for the size of the first plot. Different thresholds were tested, including means and medians at village level, Sub-County level and for the whole sample. Only village level thresholds did not yield similar results, likely because variability at village level is too little and farmers do not confine themselves to village boundaries for the acquisition of plots.

A continuous interaction term between time and susceptibility as well as between time and the size of the first plot have been tested. The results (column A of Table 4) for change in landslide susceptibility with a continuous interaction term suggest a similar trend as what was found in Table 3. The findings in Table 3 with regard to the evolution of land ownership (column B) could not be replicated with a continuous interaction term. This is likely because the relation between initial land holdings and land acquisition is not linear: only households above a certain threshold of land holdings have sufficient earnings to accumulate land faster than the others.

Table IV: Results of the regression of equation 1 with a continuous interaction term between exposure of size of the first plot on the one hand and time on the other. Household fixed effects and sampling weights are used. T-statistics are in parentheses (p < 0.10, ** p < 0.05, *** p < 0.01).*

	Column A Average **susceptibility** of land owning after this plot was acquired	Column B Total **area** of land owning after this plot was acquired
Years since first plot	-0.001	0.027***
	(-0.44)	(7.07)
Years since first plot * Susceptibility first plot	-0.010***	-0.005
	(-3.50)	(-1.07)

(cont.)		
Years since first plot *	0.003	0.014
Size first plot (cont.)	(1.19)	(1.04)
Constant	-0.090*	-0.154
	(-1.70)	(-1.51)
N	708	874
Within model R^2 (r2_w)	0.07	0.30
F statistic	5.10	25.11
p-value (F statistic)	0.00	0.00

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Risk aversion and other control variables

When setting up the research we expected that the different evolutions in landslide exposure would be driven by both actual exposure to risk and differences in individual risk preferences. The results of equation 2 testing this hypothesis are therefore presented in Table 5 (column 1 and 2). Contrary to the role of actual exposure to landslide susceptibility, little evidence could be found for a significant role of risk preferences.

This could be due to the true absence of an effect or due to problems during the elicitation of risk preferences. The risk game that has been played with the household head might have been complicated for people with a very little education. Our results could also suggest that risk games with relatively low monetary pay-offs are not able to adequately measure attitudes towards risks related to big investments in a context of near-to-subsistence agriculture[12]. Alternatively, risk preferences at the time of plot acquisition could have changed over time and might not correspond anymore with risk preferences measured at the time of the survey. Some literature argues, though, that risk preferences tend to remain stable over time (Andersen et al., 2008). Finally, if the reason for acquiring plots with a low landslide susceptibility among the most exposed households is indeed disaster avoidance, like hypothesised in our conceptual framework, prospective theory, which considers preferences for single investments, might not be the appropriate theoretical framework (Chavas, 2004).

To investigate whether our results might be influenced by plot-specific characteristics different from landslide susceptibility, equation 1 was estimated with several control variables, including plot size, distance from the house, slope steepness of the plot and a dummy for whether the plot was purchased[13]. Most of these control variables, except slope steepness, did not change the main results with regard to susceptibility (column 3 and 4 of Table 5). Slope steepness is

[12] With regard to loss aversion, the lack of significant results could also be driven by a programming mistake on our tablets allowing us to only get approximate values for loss aversion for some farmers..

[13] Also an interaction between these control variables and the time variable was tested, but this did yield different results (not shown).

strongly correlated with landslide susceptibility and its inclusion reduced the magnitude and significance of the results.

Table V: Results of the regression of equation 2 to test for the role of risk preferences (columns 1 and 2) as well as the estimation of equation 1 with additional control variables for plot characteristics (columns 3 and 4). Household fixed effects and sampling weights are used. T-statistics are in parentheses (p < 0.10, ** p < 0.05, *** p < 0.01).*

	Average **susceptibility** of land owning after this plot was acquired	Total **area** of land owning after this plot was acquired	Average **susceptibility** of land owning after this plot was acquired	Total **area** of land owning after this plot was acquired
Years since first plot	0.010***	0.032***	0.004	0.022***
	(2.67)	(3.57)	(1.28)	(4.37)
Years since first plot * Susceptibility first plot above S/C median	-0.018***	-0.014**	-0.006*	-0.012*
	(-5.30)	(-2.21)	(-1.91)	(-1.83)
Years since first plot * Size first plot above S/C median	-0.004	0.015**	-0.001	0.027***
	(-1.08)	(2.50)	(-0.27)	(4.19)
Years since first plot * σ above S/C median	0.004	-0.005		
	(0.97)	(-0.91)		
Years since first plot * α above S/C median	-0.000	0.007		
	(-0.07)	(1.00)		
Years since first plot * λ above S/C median	0.001	-0.002		
	(0.19)	(-0.32)		
Purchased [1 if yes]			-0.001	0.050
			(-0.02)	(1.13)
Plot size [Ha]			-0.017	0.663***
			(-0.42)	(4.77)
Distance between house and plot [m]			0.014	0.064
			(0.52)	(1.61)
Slope steepness on plot			0.051***	0.001
			(8.43)	(0.22)
Constant	-0.111**	-0.246**	-0.830***	-0.572***
	(-2.34)	(-2.19)	(-8.07)	(-4.03)
N	707#	873	699##	699##
Within model R^2 (r2_w)	0.06	0.32	0.42	0.50
F statistic (F statistic)	5.03	16.34	15.43	17.81
p-value	0.00	0.00	0.00	0.00

 # and ## Sample size slightly differ from previous table because we have no information on risk preferences for one of the households and no GPS location of the house for two others.

Exposure at time of acquisition

The results of Eq. 3, relating susceptibility of the new plot to exposure and land holdings at the time of acquisition, is presented in Table 6. Average exposure to landslide susceptibility does have a strong and negative correlation with the landslide susceptibility of the subsequent plot. Interesting here is that the amount of area owned before acquisition of the plot is positively correlated with the landslide susceptibility of the newly acquired plot. This is in line with the hypothesis that it is not the risk of the investment that determines acquisition behaviour, but the risk of falling below a certain income level. Farmers with more land are further from this income threshold and are therefore keener on buying plots in susceptible areas.

Table VI: Results of the estimation of equation 3. Household fixed effects and sampling weights are used. T-statistics are in parentheses (p < 0.10, ** p < 0.05, *** p < 0.01).*

	Landslide Susceptibility of acquired plot
Average susceptibility before acquisition	-1.45^{***}
	(-4.28)
Total land holdings before acqusition	0.24^{***}
	(2.84)
Constant	0.21^{**}
	(2.06)
N	222
N_groups	110
Within model R^2 (r2_w)	0.38
F statistic	16.70
p-value (F statistic)	0.00
P-value for Autocorrelation (Wooldridge test)	0.23

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

8. Discussion

This manuscript shows that farmers do make use of land acquisitions to change their exposure to landslide susceptibility. Additionally it is shown that farmers that start off their career with larger plots or plots that have a lower exposure to landslide susceptibility do manage to accumulate land faster in the course of their life. These observations suggests that land transactions in our study area are equalizing in exposure and disequalizing in total land ownings over time.

Several explanations can be put forward for this trend. The first one is in line with our hypothesis formulated earlier: farmers close to subsistence level aim at minimizing the risk of falling below a certain poverty level. If their plots have a high landslide susceptibility, they will aim at acquiring plots which have a lower exposure to landslides, be it at a higher cost. Farmers that have a plot with a low landslide susceptibility are confident of not falling below a (individual-specific) minimum consumption and can therefore acquire the more readily available plots with a high landslide susceptibility. Following this reasoning, the differential increase in land holdings between both groups can be attributed to either price differences or differences in purchasing capacity. We do have some qualitative evidence that plots that have a low exposure to landslide susceptibility are more expensive. Yet, it could also be that farmers that are exposed to landslide risk are confronted with adverse shocks due to landslides and therefore do not manage to accumulate sufficient capital to acquire land.

The landslide susceptibility of the first plots of a farmer is not independent of factors that might influence later decisions with regards to susceptibility. However, our balance tests in the appendix do not show any significant difference in household characteristics between the different groups in our data. Yet some unobserved differences might still prevail. For example, someone that was raised in a family which only has plots that are highly susceptible to landslides is very likely to inherit a plot with a high landslide susceptibility and at the same time to have strong preferences for (in case of habituation) or against (in case of bad experiences) such plots. Yet, we do not find evidence for differences in risk preferences between the different groups in our sample. Additionally, dropping the households that acquired their first plot through a purchase makes the results presented in Table 3 even stronger and more significant. As these are the households that are most likely to be subjected to endogenous selection, this suggests that what is presented in Table 3 could be a lower bound.

An alternative explanation to our findings could be that farmers which do not have plots in susceptible areas are less aware about landslides and do therefore pay less attention to signs of landslide susceptibility. This is unlikely, though, as we are talking about farmers living in the same community and thus sharing stories about landslides in the region.

One should note that not only market mechanisms and preferences of the acquiring farmer could lie at the base of the observed trends. In our sample only 33% of the first plots, and 67% of the later plots are acquired through purchases. This implies that a large part (33%) of the plots acquired after the first plot are still inherited or received. It could well be that these plots are distributed among (male) siblings with considerations of previous exposure to landslide susceptibility. There could also be preferences among the selling farmers towards selling their plots to specific farmers. Social norms could prevent people from selling susceptible land to other farmers that are already very exposed to landslides (Beck and Bjerge, 2017). However, dropping non-first plots inherited or received from our analysis makes the results stronger (see appendix, Table A.III).

Our results regarding land ownings could be driven by alternative income strategies adopted by the households that acquired small or highly susceptible plots at the beginning of their career. These households could have chosen to limit further efforts in agriculture and diversify into other businesses. While we cannot totally exclude this possibility, it is contradicted by our field observations and our data. On average the households in our sample earn 85% from their income from agriculture and the households that started with a plot that is more susceptible do not derive a smaller percentage of their income from agriculture than the others. This goes against what one would expect if the trend we observed in land ownings were driven by different income strategies.

As landslide susceptibility and slope steepness are strongly correlated in our analysis, we are not able to really ascertain that our results are driven by landslide risk alone. Other potential problems at plot level which are highly correlated with slope steepness, like erodibility and workability of the land, might also be driving our results.

Finally, there is selection bias in the sample that was used in our analysis. All households that left the region and sold their plots, as well as the households that do only have one plot are left out. A large part of the plots in our sample have been purchased (53%), while only 15% of the households mentions to have ever sold a plot. 38% of the purchased plots was acquired from someone who does not have plots in the neighbourhood anymore. Moreover, according to the respondents, 40% of the purchased plots were purchased from someone who sold it because of an urgent need for money. While underreporting of plots that have been sold or given away likely drives the strong contrast between purchasing and selling, our results suggest that a significant proportion of the plots in our sample must have been acquired from people that left agriculture altogether. We have no additional information on those that left.

9. Conclusion

Using detailed information on acquisition date, size and landslide susceptibility at plot level , this study empirically tests one of the ways through which unequal risk exposure contributes to propagating inequality in land holdings. It illustrates that farmers exposed to landslide susceptibility in our sample prefer to acquire plots that have a low landslide susceptibility, but do this at a slower pace than average. As such, initial inequality in exposure is reduced to some extent, but at the cost of an accruing inequality in total land holdings.

Our findings confirm that awareness about landslide susceptibility is high in the region and that exposure to landslide risk is not random. Literature on natural hazards finds that the poor and powerless are disproportionally exposed to natural hazards (Wisner et al., 2003). While this can be due to poor people being pushed into hazardous environments, the results of our study suggests another mechanism whereby people that are initially more exposed to natural hazards end up owning less land relative to the other farmers, but manage to reduce their exposure to landslide hazard to some extent. As such, the results of our study add to the literature on poverty traps in agriculture, whereby the rational decisions to minimize risk of falling below a certain income level are perpetuating inequality in land holdings. Previous studies used wealth as a proxy for risk of falling below a certain threshold, while we directly measure the susceptibility of facing a serious shock which can push farmers below such a level. As such we provide some concrete evidence on one of the mechanisms, i.e. exposure to natural hazards, that could be keeping farmers land poor, and hence probably also income poor.

The results nuances the findings of a previous study which suggested that land markets in Uganda decrease inequality (Baland et al., 2007). Our study highlights the importance of also considering land quality in studies about land markets and investments, rather than land quantity alone. Recognizing that processes driving inequality have nothing *natural*, like there are no *natural* disasters, more qualitative and quantitative studies are needed to further lay bare various mechanisms that can increase or decrease inequality.

Many studies on landslides tend to treat plots as given to the household and therefore fail to acknowledge the strong, endogenous processes that determine who is exposed to landslide susceptibility. The results of our study provide some evidence of the importance to consider the processes leading to certain levels of exposure as endogenous. A similar observation probably holds for erosion. This finding adds to the literature highlighting the importance of self-selection on the land market (Olbrich et al., 2012).

The costly risk reduction behaviour observed among farmers that are initially exposed to landslide susceptibility would not be necessary if functioning insurance or solidarity mechanisms would exist in our study area. Such a system would not need to systematically compensate losses due to landslides, as some farmer that are better off seem to be willing to take the risk of acquiring plots with a high landslide susceptibility. Instead it would have to compensate losses among those farmers that are close to a minimum income level. One could think of solidarity mechanisms at Sub-County level tailored towards farmers having only plots with a high susceptibility.

10. References

Andersen, S., Harrison, G.W., Lau, M.I., Rutström, E.E., 2008. Lost in State Space: Are References Stable? Int. Econ. Rev. (Philadelphia). 49, 1091–1112. doi:10.1111/j.1468-2354.2008.00507.x

Baland, J., Gaspart, F., Place, F., Platteau, J., 1999. Poverty , Tenure Security , and Access To Land in Central Uganda : the Role of Market and Non-Market 1–39.

Baland, J., Gaspart, F., Platteau, J., Place, F., 2007. The distributive impact of land markets in Uganda. Econ. Dev. … 55, 283–311.

Beck, U., Bjerge, B., 2017. Pro-poor Land Transfers and the Importance of Land Abundance and Ethnicity in The Gambia. World Dev. 99, 122–140. doi:10.1016/j.worlddev.2017.07.013

Blarel, B., Hazell, P., Place, F., Quiggin, J., 1995. The economics of land fragmentation: Evidence from Ghana and Rwanda. World Bank Econ. Rev. 6, 233–254.

Cameron, L., Shah, M., 2015. Risk-taking behavior in the wake of natural disasters. J. Hum. Resour. 50, 484–515.

Carletto, C., Gourlay, S., Murray, S., Zezza, A., 2016. Cheaper , Faster , and More Than Good Enough Is GPS the New Gold Standard in Land Area Measurement ? World Bank Policy Res. Work. Pap. Ser. 7759.

Carter, M.R., Barrett, C.B., 2006. The economics of poverty traps and persistent poverty: An asset-based approach. J. Dev. Stud. 42, 178–199. doi:10.1080/00220380500405261

Carter, M.R., Lybbert, T.J., 2012. Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso. J. Dev. Econ. 99, 255–264.

doi:10.1016/j.jdeveco.2012.02.003
Chavas, J.P., 2004. Risk Analysis in Theory and Practice, Academic Press Advanced Finance Series.
Collins, T.W., 2009. The production of unequal risk in hazardscapes: An explanatory frame applied to disaster at the US–Mexico border. Geoforum 40, 589–601. doi:10.1016/j.geoforum.2009.04.009
Deininger, K., 2003. Land markets in developing and transition economies: Impact of liberalization and implications for future reform. Am. J. Agric. Econ. 85, 1217–1222.
Deininger, K., Ali, D.A., 2008. Do Overlapping Land Rights Reduce Agricultural Investment? Evidence from Uganda. Am. J. Agric. Econ. 90, 869–882. doi:10.1111/j.1467-8276.2008.01171.x
Deininger, K., Ali, D.A., Yamano, T., 2008. Legal Knowledge and Economic Development : The Case of Land Rights in Uganda. Land Econ. 84, 593–619. doi:10.1353/lde.2008.0010
Deininger, K., Castagnini, R., 2006. Incidence and impact of land conflict in Uganda. J. Econ. Behav. Organ. 60, 321–345. doi:10.1016/j.jebo.2004.04.008
Deininger, K., Jin, S., Nagarajan, H.K., 2009. Determinants and Consequences of Land Sales Market Participation: Panel Evidence from India. World Dev. 37, 410–421. doi:10.1016/j.worlddev.2008.06.004
Dercon, S., 2006. Vulnerability: a micro perspective. Secur. Dev. an Unstable World 30, 117–146.
Dercon, S., 1998. Wealth, risk and activity choice: cattle in Western Tanzania. J. Dev. Econ. 55, 1–42. doi:10.1016/S0304-3878(97)00054-0
Gloede, O., Menkhoff, L., Waibel, H., 2015. Shocks, Individual Risk Attitude, and Vulnerability to Poverty among Rural Households in Thailand and Vietnam. World Dev. 71, 54–78. doi:10.1016/j.worlddev.2013.11.005
Goldstein, M., Udry, C., 2008. The Profits of Power: Land Rights and Agricultural Investment in Ghana. J. Polit. Econ. 116, 981–1022. doi:10.1086/595561
Jacobs, L., Dewitte, O., Poesen, J., Delvaux, D., Thiery, W., Kervyn, M., 2016. The Rwenzori Mountains, a landslide-prone region? Landslides 13, 519–536. doi:10.1007/s10346-015-0582-5
Jacobs, L., Dewitte, O., Poesen, J., Maes, J., Mertens, K., Sekajugo, J., Kervyn, M., 2017. Landslide characteristics and spatial distribution in the Rwenzori Mountains, Uganda. J. African Earth Sci. 1–9. doi:10.1016/j.jafrearsci.2016.05.013
Kahneman, D., Tversky, A., 1979. Prospect Theory : An Analysis of Decision under Risk. Econometrica 47, 263–292.
Katz, E.G., Baxter, M., Davis, S., Goldman, M., Melmed-, J., Thiesenhusen, B., Stanley, D., 2000. Social Capital and Natural Capital : A Comparative Analysis of Land Tenure and Natural Resource Management in Guatemala. Land Econ. 76, 114–132.
Kilic, T., Zezza, A., Carletto, C., Savastano, S., 2013. Missing(ness) in Action Selectivity Bias in GPS-Based Land Area Measurements. World Bank Policy Res. Work. Pap. Ser. 6490.
Kim, N., 2012. How much more exposed are the poor to natural disasters? Global and regional measurement. Disasters 36, 195–211. doi:10.1111/j.1467-7717.2011.01258.x
Loewenstein, G., Angner, E., 2003. Predicting and Indulging Changing Preferences, in: Loewenstein, G., Read, D., Baumeister, R.F. (Eds.), Time and Decision. Economic and Psychological Perspectives on Intertemporal Choice. Russell Sage Foundation, New York.
Lybbert, T.J., Barrett, C.B., Desta, S., Coppock, D.L., 2004. Stochastic wealth dynamics and risk management among a poor population. Econ. J. 114, 750–777. doi:10.1111/j.1468-

0297.2004.00242.x
Mertens, K., Jacobs, L., Maes, J., Kabaseke, C., Maertens, M., Poesen, J., Kervyn, M., Vranken, L., 2016. The direct impact of landslides on household income in tropical regions: A case study from the Rwenzori Mountains in Uganda. Sci. Total Environ. 550, 1032–1043. doi:10.1016/j.scitotenv.2016.01.171
Mertens, K., Jacobs, L., Maes, J., Poesen, J., Kervyn, M., Vranken, L., 2017. Disaster risk reduction among households exposed to landslide hazard: a crucial role for coping appraisal? under Rev.
Morduch, J., 1995. Income Smoothing and Consumption Smoothing. J. Econ. Perspect. 9, 103–114.
Olbrich, R., Quaas, M.F., Haensler, A., Baumgärtner, S., 2012. Risk preferences under heterogeneous environmental risk (No. 208), Working Paper Series in Economics.
Omura, M., 2008. Property rights and natural resource management incentives: Do transferability and formality matter? Am. J. Agric. Econ. 90, 1143–1155. doi:10.1111/j.1467-8276.2008.01151.x
Petley, D., 2012. Global patterns of loss of life from landslides. Geology 40, 927–930. doi:10.1130/G33217.1
Place, F., 2009. Land Tenure and Agricultural Productivity in Africa: A Comparative Analysis of the Economics Literature and Recent Policy Strategies and Reforms. World Dev. 37, 1326–1336. doi:10.1016/j.worlddev.2008.08.020
Rao, X., 2014. Land Fragmentation with Double Bonuses -- The Case of Tanzanian Agriculture, in: Selected Poster/Paper Prepared for Presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, Minnesota, 27-29 June 2014.
Rosenzweig, M.R., Binswanger, H.P., 1993. Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments. Econ. J. 103, 56. doi:10.2307/2234337
Sawada, Y., Takasaki, Y., 2017. Natural Disaster, Poverty, and Development: An Introduction. World Dev. 94, 2–15. doi:10.1016/j.worlddev.2016.12.035
Tanaka, T., Camerer, C.F., Nguyen, Q., 2016. Risk and time preferences: Linking experimental and household survey data from Vietnam. Behav. Econ. Prefer. Choices, Happiness 100, 3–25. doi:10.1007/978-4-431-55402-8_1
The World Bank, 2000. Designing household survey: Questionnaires for developing countries.
UNISDR, 2015. Sendai Framework for Disaster Risk Reduction 2015-2030. Geneva.
van Leeuwen, M., 2014. Renegotiating customary tenure reform – Land governance reform and tenure security in Uganda. Land use policy 39, 292–300. doi:10.1016/j.landusepol.2014.02.007
Wisner, B., Blaikie, P., Cannon, T., Davis, I., 2003. At risk: natural hazards, people's vulnerability and disasters (Part 1), in: At Risk: Natural Hazards, People's Vulnerability and Disasters. p. 134.
Wolgin, J.M., 1975. Resource allocation and risk: A case study of smallholder agriculture in Kenya. Am. J. Agric. Econ. 57, 622–630.
Young, D.L., 1979. Resource allocation and risk: A case study of smallholder agriculture in Kenya: Comment. Am. J. Agric. Econ. 61, 111–113.
Zimmerman, F.J., Carter, M.R., 2003. Asset smoothing, consumption smoothing and the reproduction of inequality under risk and subsistence constraints. J. Dev. Econ. 71, 233–260. doi:10.1016/s0304-3878(03)00028-2

11. Appendix

Table A.I presents a balance test on the sample of households split according to whether susceptibility on the first plot is above or below Sub-County median. Of course, a significant difference exists between both groups with regard to the susceptibility on the first plot and the average susceptibility on all the plots. Yet, for the other household characteristics, both groups are surprisingly similar.

Table A.I: Descriptive statistics of the whole sample and of those households (HH) for whom the susceptibility on the first plot is below Sub-County median (Group 1) and of those for whom the susceptibility on the first plot is above the Sub-County median (Group 2). T-test have been run to test balance on observables between groups ($p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).*

	All	Group 1 HH with susceptibility on first plot below S/C median	Test	Group 2 HH with susceptibility on first plot above S/C median
Household characteristics at the time of the survey				
Age household (HH) head	46.56 (15.39)	45.63 (14.32)		46.52 (16.10)
Years of formal education HH head	5.77 (4.04)	5.70 (3.79)		5.55 (3.77)
Adult equivalents (OECD scales)	3.50 (1.19)	3.54 (1.19)		3.45 (1.18)
Total area owned [Ha]	1.21 (1.25)	1.12 (1.26)		1.07 (0.80)
Number of plots owned	3.05 (1.94)	2.91 (1.88)		2.85 (1.55)
Number of plots purchased	1.54 (1.73)	1.52 (1.75)		1.29 (1.42)
Number of plots ever sold or given away	0.22 (0.66)	0.18 (0.55)		0.20 (0.69)
Average distance between plots [m]	536 (650)	497 (637)		587 (694)
Average landslide susceptibility at the time of the survey [min: -2.3; med: 0.15; max: 1.8]	-0.14 (0.90)	-0.54 (0.85)	***	0.35 (0.68)
Average landslide susceptibility on non-first plots at the time of the survey [min: -2.3; med: 0.13; max: 2.04]	-0.11 (0.97)	-0.24 (1.00)	***	0.15 (0.90)
σ (risk aversion) Higher value = more risk averse [min: 0.1; med: 0.7; max: 1.5]	0.89 (0.53)	0.90 (0.52)		0.92 (0.53)
α (shape of the probability weighting function) α < 1 : overweighting small probabilities [min: 0.1; med: 0.8; max: 1.5]	0.82 (0.37)	0.84 (0.39)		0.81 (0.35)
λ (loss aversion) λ > 1 : loss averse# [min: 0.1; med: 1.75; max: 10]	2.66 (3.07)	2.63 (3.11)		2.49 (2.95)
Characteristics first plot				
LS susceptibility on first plot [min: -2.2; med: 0.17; max: 1.8]	-0.09 (0.96)	-0.69 (0.84)	***	0.50 (0.68)
Size first plot [Ha]	0.46 (0.51)	0.46 (0.58)		0.45 (0.42)
Age HHH when acquired first plot	24.28 (12.18)	23.18 (10.63)	*	25.70 (13.39)

First plot purchased [1 if yes]	0.32 (0.47)	0.30 (0.46)	0.32 (0.47)
Percentage of plots that are not mapped	0.19 (0.26)	0.15 (0.24)	0.13 (0.21)
Observations (# HHs)	397	176	176

A balance test on the sample of households split according to whether the size of the first plot is above or below Sub-County median is shown in Table A.II. It is clear that some significant differences exist between both groups of households. Famers that started with a more-than-median plot size are on average older, have bigger families and own more land, but less plots. The average distance between their house and plots is also smaller among farmers that started with a big plot. The difference in age and family size reflects the trend of decreasing plot sizes for beginning farmers due to increasing population pressure in the region.

Table A.II: Descriptive statistics of the whole sample and of those households for whom the size of the first plot is below Sub-County median (Group 1) and of those for whom the size of the first plot is above the Sub-County median (Group 2). T-test have been run to test balance on observables between groups (p < 0.10, ** p < 0.05, *** p < 0.01).*

	All	Group 1 HH with size of first plot below S/C median	Test	Group 2 HH with size of first plot above S/C median
Household characteristics at the time of the survey				
Age household (HH) head	46.56 (15.39)	44.48 (14.16)	***	48.68 (16.32)
Years of formal education HH head	5.77 (4.04)	5.65 (3.61)		5.89 (4.44)
Adult equivalents (OECD scales)	3.50 (1.19)	3.36 (1.10)	**	3.64 (1.26)
Total area owned [Ha]	1.21 (1.25)	0.77 (0.74)	***	1.65 (1.49)
Number of plots owned	3.05 (1.94)	3.23 (2.03)	*	2.87 (1.83)
Number of plots purchased	1.54 (1.73)	1.59 (1.80)		1.49 (1.66)
Number of plots ever sold or given away	0.22 (0.66)	0.20 (0.55)		0.24 (0.76)
Average distance between plots [m]	536 (650)	606 (784)	*	455 (440)
Average exposure to landslide susceptibility at the time of the survey	-0.14 (0.90)	-0.21 (0.88)		-0.08 (0.92)
Average landslide susceptibility on non-first plots at the time of the survey	-0.11 (0.97)	-0.14 (0.95)		-0.08 (1.00)
σ (risk aversion) Higher value = more risk averse	0.89 (0.53)	0.86 (0.54)		0.91 (0.51)
α (shape of the probability weighting function) α < 1 : overweighting small probabilities	0.82 (0.37)	0.85 (0.37)		0.80 (0.36)
λ (loss aversion) λ > 1 : loss averse#	2.66 (3.07)	2.79 (3.23)		2.54 (2.91)
Characteristics first plot				
LS susceptibility on first plot	-0.09 (0.96)	-0.18 (0.97)		-0.01 (0.96)
Size first plot [Ha]	0.46 (0.51)	0.18 (0.09)	***	0.74 (0.59)
Age HHH when acquired first plot	24.28 (12.18)	23.61 (11.54)		24.96 (12.80)

First plot purchased [1 if yes]	0.32 (0.47)	0.32 (0.47)	0.32 (0.47)
Percentage of plots that are not mapped	0.19 (0.26)	0.20 (0.27)	0.18 (0.25)
Observations (# HHs)	397	340	57

In Table A.III we reproduced the results of the analysis that was presented in Table III, but dropped non-first plots that were not purchased. We included this table here to show that the trend that is being found in the main body of the manuscript can indeed be attributed to the land markets, and not to some other trend of inheritance or the exchange of gifts. Results regarding the evolution of susceptibility are similar, while results on the divergence in land ownings are stronger than what is presented in Table III.

Table A.III: regression results of equation 1 with real data (column A and C) and simulated data (column A) after dropping non-first plots that have not been purchased. Household fixed effects and sampling weights are used. T-statistics are in parentheses (p < 0.10, ** p < 0.05, *** p < 0.01).*

	Column A Average **susceptibility** of land ownings after this plot was acquired	Column B Simulated average susceptibility if acquisition was random and spatial correlation of 0.5 in susceptibility	Column C Total **area** of land owning after this plot was acquired
Years since first plot	0.011** (2.59)	0.005** (2.16)	0.033*** (4.36)
Years since first plot * Susceptibility first plot above S/C median	-0.016*** (-3.97)	-0.010*** (-4.53)	-0.019** (-2.31)
Years since first plot * Size first plot above S/C median	-0.003 (-0.83)	-0.003 (-1.39)	0.020*** (2.70)
Constant	-0.119** (-2.37)	-0.052* (-1.86)	-0.305** (-2.52)
N	597	597	715
Within model R^2 (r2_w)	0.05	0.13	0.33
F statistic	5.33	10.64	26.04
p-value (F statistic)	0.00	0.00	0.00

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

An illustration of the evolution of land holdings over the lifetime of a farmer is given in Figure A.1. It is clear that very different pathways are being followed by farmers that are initially exposed and farmers that are initially less exposed to landslide susceptibility. The graph also shows that initial landholdings are similar across both groups. A similar graph for landslide susceptibility does not give such visually appealing results because differences in landslide susceptibility across the Sub-County are larger than between farmers within Sub-Counties.

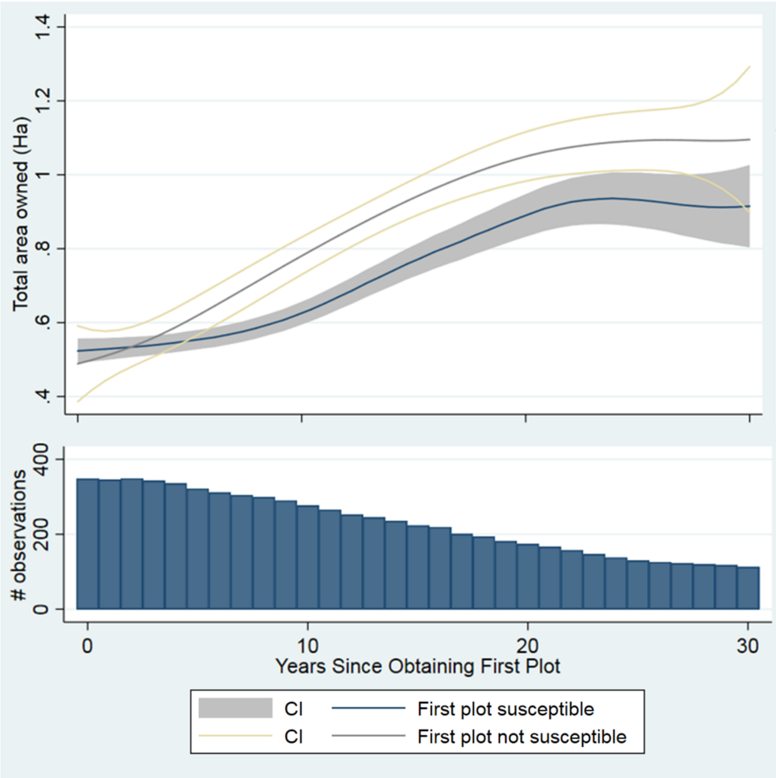

Figure A.1: Local polynomial smooth on the evolution of land holdings over the lifetime of farmers that started with a plot with a high landslide susceptibility and for farmers that started with a plot with a low landslide susceptibility (first panel). The second panel illustrates how many observations are being used for the estimation of land holdings at every point in time. Since the dataset contains farmers of various ages, the number of observations reduces with increasing recall time. This also explains the expanding confidence interval with increasing recall time. An epanechnikov Kernel function was used.