TUM School of Social Sciences and Technology

TUM School of Management

Munich Papers in Political Economy

Working Paper No. 04/2024

Trapped in Poverty: The Impact of Large-Scale Land Acquisitions on Education. A Geospatial Approach

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August 2024

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Abstract

Large parts of the population in developing countries depend on agriculture for their income and food security. However, agriculture-dependent households are vulnerable to agricultural shocks, which prevent them from investing in education, thus hindering their socio-economic progress and their ability to reduce dependence on agriculture. Research on the impact of agricultural shocks on education predominantly focuses on those caused by extreme weather events and fluctuations in agricultural commodity prices. The impact of large-scale land acquisitions on education has not been studied, despite their growing number and potential to disrupt the agricultural production of small-scale farmers. This paper fills the research gap by hypothesizing that large-scale land acquisitions negatively impact the education of people in their vicinity due to resulting food insecurity and income loss, leading households to divert educational resources to basic needs and withdraw children from school to contribute to income. The negative impact on education is expected to be more pronounced for boys, who find rural employment more easily and are thus more frequently withdrawn from school. Employing a geospatial approach, this paper links 322 large-scale land acquisitions in Africa to 46,711 Afrobarometer respondents. The results of the regression analysis indicate that being affected by a large-scale land acquisition between the ages of 0 and 16 has a statistically significant negative impact on education. The hypothesized stronger negative impact on male education is not supported by the results. The findings imply that large-scale land acquisitions hinder rural development and entrench poverty, contrary to claims by investors and politicians.

Keywords: Education, large-scale land acquisition, agricultural shocks, rural development

JEL Codes: I20, I24,I25

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1. Introduction

Education is a key determinant of socio-economic outcomes like income (Hofmarcher, 2021), political participation (Bömmel & Heineck, 2023), and health (Davies et al., 2023). Improving access to education is a central goal of the United Nations' 2030 Agenda for Sustainable Development (Filho et al., 2023). However, access to education in developing countries[1] remains limited, with approximately 260 million children eligible for primary and secondary schooling not enrolled. In sub-Saharan Africa, only two-thirds of children complete primary education. Additionally, developing countries are characterized by significant gender disparities in education that disproportionately disadvantage girls (BMZ, 2024).

For households whose livelihoods depend on agriculture, investing regularly and sustainably in education is particularly difficult. Agricultural shocks—disruptions in agricultural income and production (Alam et al., 2020)—lead to volatility in yields and earnings. Agriculture is the primary livelihood for large parts of the population in developing countries. In 2019, 48.1% of the working population in Africa and 29% in Asia were employed in the agricultural sector. More than 2 billion people in developing countries live in households whose livelihoods depend on agriculture (Davis et al., 2023). Given the importance of agriculture in developing countries, agricultural shocks prevent large segments of the population from improving their socio-economic situation by investing in education. This reinforces dependence on agriculture, trapping households in a cycle of poverty and potentially exacerbating existing educational gender disparities (Björkman-Nyqvist, 2013).

Research on the impact of agricultural shocks on education primarily focuses on agricultural shocks caused by weather and climate conditions, as well as those resulting from decreasing prices for agricultural commodities (Alam et al., 2020). So far, the literature has not addressed agricultural shocks caused by large-scale land acquisitions (LSLAs), defined as land purchases

[1] I use the term developing countries, because it is used in the literature on agricultural shocks. The term typically refers to low and middle-income countries, but there is no uniform definition, making it vague (Farias, 2023).

by investors[2] (D'Odorico et al., 2017). Investors increasingly buy land in developing countries that was previously used by small-scale farmers and secured the livelihoods of the rural population (Dell'Angelo et al., 2021). The small-scale farmers lose access to the land, leading to disruptions in agricultural income and production. This has far-reaching consequences for the affected communities and farmers, causing income loss (Yengoh & Armah, 2015), food insecurity (Castet, 2024), and conflicts (Balestri & Maggioni, 2021). The number of LSLAs is increasing rapidly. Investors have globally purchased an estimated 90 million hectares of fertile land since the early 2000s. This land has the capacity to provide food for up to 330 million people (Müller et al., 2021). Most of the purchased land is used for export-oriented agriculture or land speculation (Dell'Angelo et al., 2017).

Given the significance of education as a key socioeconomic predictor, the extensive dependence on agricultural livelihoods in developing countries, and the increasing number of LSLAs, this paper addresses the following research question: *What is the impact of LSLAs on education?*

As my primary hypothesis, I argue that LSLAs negatively affect the education of people living in their vicinity through two mechanisms: loss of income and food insecurity. Once the purchased land is put into production, LSLAs deprive individuals of land access, preventing them from growing crops. This results in increased food insecurity and decreased income. Consequently, households redirect funds from education to cover essential needs, thereby reducing their educational investments. Additionally, it compels households to withdraw their children from school so they can contribute to household income through work. As a secondary hypothesis, I argue that the detrimental effects of LSLAs on education are more pronounced for males than for females. Since it is easier for males to find employment in rural areas, they are more likely to be withdrawn from school.

To test the hypotheses, I employ a geospatial research design. My analysis is based on 322 LSLAs in Africa from the Land Matrix database and 46,711 respondents from the sixth round

[2] The term large-scale land acquisitions is the most commonly used term in literature dealing with land deals. Some papers refer to it as land grabbing or land rush, but these terms have been criticized for being too biased and suggestive. A key aspect of these terms is that they refer to land purchases by investors, distinguishing them from land trading between private individuals and small-scale farmers. The investors can be domestic or foreign investors (D'Odorico et al., 2017). This is how the term is also used in this paper. Individual land transactions are then referred to as a Large-scale land acquisition (LSLA).

of Afrobarometer. I calculate the period during which the respondents were aged 0 to 16 and determine if they were affected by an LSLA during this time. Since LSLAs are not randomly distributed, I differentiate between active LSLAs, where the land is utilized by investors, and inactive LSLAs, where the land, though purchased, remains unused by investors and thus available to small-scale farmers. This distinction enables me to address the non-random distribution of LSLAs by controlling for the selection bias (Wegenast et al., 2022).

The results from the subsequent OLS regression analysis show that being affected by an active LSLA between the ages of 0 and 16 has a statistically significant negative impact on education. However, the hypothesized stronger negative impact on the education of males is not supported.

This paper makes several contributions to existing research. It contributes to the literature on agricultural shocks while simultaneously broadening the understanding of the socio-economic consequences of LSLAs. Furthermore, it examines the gendered impact of LSLAs, an aspect that has been neglected in the literature, and at the same time, it adds to the body of research that addresses the gendered impacts of agricultural shocks. Additionally, this paper contributes methodologically to the LSLA literature. Most existing LSLA studies are case studies, while geospatial studies are rare, despite their potential to analyze the local consequences of LSLAs.

The paper is structured as follows: Chapter 2 reviews relevant literature and identifies the research gaps this paper aims to address. Chapter 3 outlines the theoretical framework. Chapter 4 describes the research design. Chapter 5 presents the analysis. Chapter 6 focuses on conducting robustness checks and testing the causal mechanisms. Chapter 7 discusses the results, and Chapter 8 concludes with reflections on the findings and suggestions for future research.

2. Literature Review

I divide the literature review into two parts. First, I situate the paper within the literature on agricultural shocks and education, also addressing the gendered impact of agricultural shocks on education. I then provide a brief overview of the literature on LSLAs, as this paper addresses various research gaps in that literature.

2.1. Agricultural Shocks and Education

Most of the literature on agricultural shocks and their impact on education deals either with agricultural shocks caused by weather and climate conditions or with agricultural shocks caused by the price decline of agricultural commodities (Alam et al., 2020).

Weather and climate-induced agricultural shocks, such as droughts, floods, or extreme temperature fluctuations, negatively impact the education of those relying on agricultural livelihoods by decreasing agricultural production, which leads to reduced household income and lower educational investment (Miller et al., 2024). Additionally, the income loss often compels families to withdraw children from school to support household finances and mitigate the effects of these shocks (Beegle et al., 2006; Alam et al., 2020). Many small-scale farmers in developing countries are subsistence farmers without a regular income, so the negative impact of weather-induced climate shocks on them comes primarily from the resulting food insecurity (Kinda, 2016; Fusco, 2022). Food insecurity not only directly impairs children's cognitive performance and increases their risk of dropping out of school (Tamiru et al., 2016), but it also compels affected households to withdraw children from school to seek additional income (Bandara et al., 2015). Furthermore, many children are too hungry to attend school, opting instead to search for food (Belachew et al., 2011). The effects of these shocks are profound; for example, Agamile and Lawson (2021) report that rainfall below the local historical average reduces school attendance in Uganda by up to 10%. Similarly, Nübler et al. (2021) observe that lack of rainfall negatively affects both school enrollment and test scores in Kenya, a trend that persists even if the shock occurs before children reach school age, as households struggle to recover from the economic setbacks induced by the shock.

Another research area examines the impact of declining agricultural commodity prices on education. Falling agricultural commodity prices compel farmers to sell their crops for less, which in turn reduces household income (Brown et al., 2023). As financial resources for education decrease, families are forced to pull children from school to contribute to household income through work and cut back on educational investments (Beck et al., 2019). For example, Asfaw (2018) observed that the 2008 global price drop in coffee led to increased dropout rates among children aged 15-18 in Ethiopian coffee-producing villages. Similarly, Cogneu and Jedwab (2012) reported that the 1990 cocoa price drop in the Ivory Coast resulted in lower school enrollment rates among children in cocoa-producing households.

In developing countries, girls often have less access to education compared to boys, and agricultural shocks can exacerbate these gender disparities (Björkman-Nyqvist, 2013). However, the evidence regarding the differential impact of agricultural shocks on the education of boys and girls remains inconclusive, as outcomes vary based on local conditions and prevailing gender norms. While households may prioritize boys' education, girls often cannot contribute as significantly to household income through labor because of a preference for boys in the labor market (Brown et al., 2023). Research findings highlight cross-regional differences: Beegle et al. (2008) observed that in Tanzania, rainfall shocks negatively affect boys' education more severely. In contrast, Maitra and Tagat (2019) found that in India, girls are predominantly affected by rainfall shocks. Similarly, Björkman-Nyqvist (2013) reported that in Uganda, rainfall shocks disproportionately harm girls' academic performance, as households tend to allocate scarce educational resources preferentially to boys. Lastly, Sen and Villa (2022) discovered that in South Africa, delayed rainfall affects both genders equally.

To the best of the authors' knowledge, no research has examined the impact of LSLAs on education, despite LSLAs constituting a significant agricultural shock by disrupting the agricultural production of small-scale farmers. Additionally, LSLAs impact small-scale farmers as unexpectedly as agricultural shocks induced by weather conditions and declining prices for agricultural commodities. Small-scale farmers are unprepared when production starts on the purchased land, as they usually have no knowledge of the sale of the land because they are working under unclear ownership conditions and are not consulted or informed in advance of the start of production (Vermeulen & Cotula, 2010). Furthermore, studies show that LSLAs lead to income loss (Kebede et al., 2021) and food insecurity (Castet, 2024), the two mechanisms through which agricultural income shocks induced by weather and climate and agricultural income shocks induced by the price decline of agricultural commodities negatively affect education. Given the widespread prevalence of LSLAs in developing countries, it is therefore relevant that the literature on agricultural shocks and education also considers the impact of agricultural shocks induced by LSLAs.

2.2. Determinants and Consequences of LSLAs

The literature can be divided into two main strands: one that explores the determinants of LSLAs and another that examines the consequences of LSLAs for affected communities and small-scale farmers.

Investors typically target areas with favorable soil and climate conditions for agriculture (D'Odorico et al., 2017). They often purchase land where ownership rights are ambiguous and poorly enforced (Yengoh et al., 2016). Land owned by women, who have weaker property rights in many regions, is particularly attractive to investors (Wegenast et al., 2022). Similarly, land belonging to marginalized population groups also attracts LSLAs, as these groups usually lack the political leverage to effectively resist such acquisitions (Moreda, 2017).

Most research on the consequences of LSLAs focuses on the impact of LSLAs on income and food security. LSLAs diminish the food security of individuals living nearby because they lose access to the land they previously cultivated to sustain themselves (Castet, 2024). This also leads to a loss of income for the affected small-scale farmers (Kebede et al., 2021). Despite frequent claims by international actors about job creation through LSLAs, empirical evidence to support this assertion is scant (D'Odorico et al., 2017). Wegenast et al. (2022) note that few studies explore the gendered impacts of LSLAs, even though women, who frequently lack land titles, constitute a significant portion of small-scale farmers. The limited research available suggests that women face greater income losses from LSLAs than men (Yengoh & Armah, 2015) and are forced into more time-consuming tasks like collecting wood and fetching water, which negatively affects their household status (Hajjar et al., 2020).

Some papers find a positive influence of LSLAs on surrounding communities, especially when investors involve locals in agricultural production (Dell'Angelo et al., 2017). Yet, this highlights another issue with the literature on the consequences of LSLAs: it primarily relies on qualitative case studies, whose results are contingent on the specific characteristics of each investment and do not allow for the identification of systematic local relationships (Yang & He, 2021; Wegenast et al., 2022). The infrequent large-N studies often use the aggregated number of LSLAs at the country level as the independent variable (e.g. Brandl et al., 2021), which is inappropriate because the impacts of LSLAs are predominantly local (Hufe & Heuermann, 2017). Geospatial studies are scarce, despite their potential to analyze systematic local effects of LSLAs. Notable exceptions are Wegenast et al. (2022) and Balestri & Maggioni (2019), who show that LSLAs erode family trust and increase conflicts, respectively.

To summarize, this paper makes several contributions to the existing literature. First, it contributes to the literature dealing with the impact of agricultural shocks on education by expanding the focus of this literature to include agricultural shocks induced by LSLAs. Second, it extends the literature on the socio-economic consequences of LSLAs. Furthermore, the paper explores whether LSLAs have a gendered impact on education. Thus, this paper also contributes to the inconclusive literature on the gendered impacts of agricultural shocks. Methodologically, this paper extends beyond the prevalent case studies in LSLA research by using a geospatial approach.

3. Theory

In the following, I present the theoretical explanations regarding the influence of LSLAs on education. I first argue that LSLAs have a negative impact on education through income loss and food insecurity. These mechanisms are interconnected. Income loss can increase food insecurity, but food insecurity alone also undermines education, especially for subsistence farmers. In the second part, I argue that withdrawing children from school to mitigate the adverse effects of LSLAs disproportionately affects boys, resulting in a larger negative impact on their education.

3.1. The Impact of LSLAs on Education

LSLAs lead to income loss for small-scale farmers and surrounding communities. Farmers lose access to the land, preventing them from growing and selling crops (Yengoh & Armah, 2015). Although international investors claim that LSLAs generate employment, evidence often contradicts these assertions, showing that the land is predominantly used for export-oriented and mechanized agriculture, which creates few jobs (Dell'Angelo et al., 2017; Wegenast et al., 2022). The jobs that do arise, such as those in agricultural machinery maintenance, typically require skills not possessed by the local rural population (Sekoai & Yoro, 2016).

Furthermore, LSLAs reduce income even for households not directly dependent on the sold land. The post-acquisition use of land for export-oriented agriculture, biofuel production, or renewable energy creation reduces food availability for local markets and drives up local food prices. This forces households to spend more on food, thereby reducing their income. Müller et al. (2021) found that in areas affected by LSLAs, dietary diversity scores of children under five years old declined, indicating reduced availability of local foods.

The loss of income due to LSLAs means that households have fewer financial resources to invest in education. In addition, households withdraw children from school to compensate for income loss through additional work when faced with an agricultural shock (Alam et al., 2020). This occurs even when schooling is free, as there are still substantial associated costs, such as transportation and school materials. For instance, in Africa, school expenses can account for up to 25% of a household's budget (Brown et al., 2023).

Food insecurity is the second mechanism through which LSLAs can negatively affect education. While food insecurity can result from the income loss associated with LSLAs, many small-scale farmers in Africa rely not on regular income, but on consuming the crops they cultivate. The loss of land due to LSLAs prevents them from growing crops for their own consumption, exacerbating food insecurity (Giller et al., 2021). For instance, Kebede et al. (2023) found that individuals affected by LSLAs in Ethiopia had a daily calorie intake 23% lower than that of a control group. Food insecurity impacts education by impairing cognitive performance and increasing dropout risk. Children must also spend time searching for food, reducing time spent on education (Tamiru et al., 2016). Furthermore, like income loss, food insecurity can lead households to withdraw children from school to help generate income and mitigate food shortages (Belachew et al. 2011). My arguments lead to the following hypothesis:

H1: *LSLAs negatively impact the education of people living in their vicinity.*

3.2. The Gendered Impact of LSLAs on Education

As outlined in the literature review, the evidence regarding the gendered impact of agricultural shocks on education is inconclusive. However, research indicates that when a community loses access to land due to an LSLA, men are more likely to secure jobs in rural areas (Hajjar et al., 2020). Conversely, women struggle to find alternative employment opportunities. They face limited options outside agriculture, as men are often preferred for physical labor, and many non-agricultural jobs also require hard physical work (Yengoh & Armah, 2015).

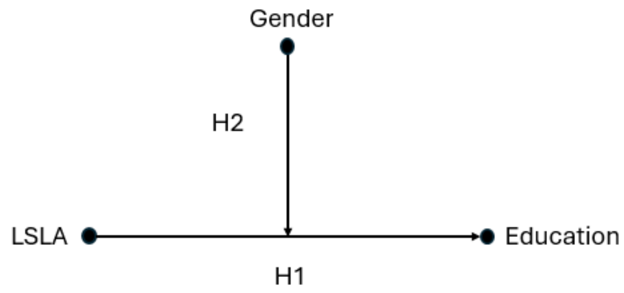
I argue that the fact that women often have fewer employment opportunities than men in rural areas means that the negative impact of LSLAs on education is more pronounced for men because men are more able to contribute to household income through work and thus can no longer attend school. Given the substantial agricultural shock resulting from LSLAs, I contend that the pressure imposed by LSLAs—through income loss and heightened food insecurity—leads households to disregard existing gender-specific educational preferences. Supporting this, research indicates that in Sub-Saharan Africa, where many LSLAs occur, households abandon these preferences when faced with substantial income shocks, with families frequently withdrawing boys from school due to their greater potential to contribute to household income (Brown et al., 2023). An aspect that reinforces my theory is that agricultural shocks induced by LSLAs are irrecoverable for small-scale farmers in the long term, unlike other agricultural shocks, because they result in permanent loss of land access. Therefore, farmers cannot simply endure the consequences of LSLAs while maintaining their gender-specific preferences; instead, they must immediately and permanently seek new sources of income. This leads to the following hypothesis.

H2: *The negative impact of LSLAs on education is more pronounced for males.*

4. Research Design

I analyze the two hypotheses, depicted in Figure 1, in the African context for three reasons. First, education remains a critical challenge for African governments; only 70% of African children finish primary school, and just 30% complete lower secondary school (Brown et al., 2023). Second, Africa is a major target for LSLAs. Between 2005 and 2020, land purchased by investors in Africa increased from 1 million to 7.3 million hectares, with 56% of this land previously used by small-scale farmers and pastoralists, securing livelihoods for much of the rural population (Wegenast et al., 2022). Third, the agricultural sector is the most important employment sector in Africa, providing the basis for income and food security for significant parts of the population (Davis et al., 2023).

Figure 1: Hypotheses



Note: Created by the author.

I employ a geospatial research design to test the hypotheses, using data from 46,711 respondents from the sixth round of Afrobarometer and 322 LSLAs from the Land Matrix database. The analysis is conducted at the individual respondent level.

The sixth round of the Afrobarometer is the most recent geocoded round. Afrobarometer uses a clustered, stratified, multi-stage area probability sampling design to create a representative cross-section of voting-age citizens in each country (Afrobarometer, 2024). Respondents are interviewed within enumeration areas, the smallest geographical units with population data, which are geocoded to assign coordinates to each respondent (BenYishay et al., 2017).

The Land Matrix[3] database contains geodata on LSLAs worldwide, primarily derived from public sources such as newspapers and government reports. It includes LSLAs involving the transfer of land rights through sale, lease, or concession, typically covering at least 200 hectares. In some countries, such as Uganda, Senegal, and Cameroon, LSLAs covering only 50 hectares are included (Land Matrix, 2024).

I start by discussing the identification strategy and data selection together, as the identification strategy is crucial for comprehending the data selection and the subsequent discussions on the operationalization of the variables and model specification.

[3] The Land Matrix database is a joint project of the German Corporation for International Cooperation (GIZ), the Centre for Development and Environment of the University of Bern, the German Institute for Global and Area Studies and the International Land Coalition (Land Matrix, 2024).

4.1. Identification Strategy and Data Selection

I calculated for each respondent the period the respondent was between 0 and 16 years old ($0 = Survey\ Year - Respondent\ Age; 16\ = 0 + 16$), as LSLAs can only negatively affect education if respondents had not completed their education at the time of the land purchase. I use 0 as the lower bound because agricultural shocks at birth negatively affect education, with households taking a long time to recover financially and consequently not sending children to school initially (Nübler et al., 2021). I use 16 as the upper bound due to the structure of my data. The Afrobarometer surveys were conducted in 2014 and 2015. Therefore, I only include LSLAs where the investor purchased the land by 2013. If I used 18 as the upper bound, the 0-18 year period for some younger respondents would extend beyond 2013, where I no longer consider LSLAs. This would result in a shorter effective time period for younger respondents compared to older respondents whose periods do not extend beyond 2013. Reducing the timeframe is not possible, as it would result in too few respondents being affected by LSLAs. The negative impact of agricultural shocks on education are persistent (Nübler et al., 2021). Therefore, the negative impact of LSLAs on education, when respondents were between 0 and 16 years old, can be observed in their education levels at the time of the Afrobarometer survey.

Next, I converted both the Afrobarometer and Land Matrix data sets into *simple feature objects* using the *simple features* R package. Then, I harmonized the coordinate systems of both data sets using the Mercator coordinate system with the identifier 32732. Afterwards, I created buffers around the LSLAs.

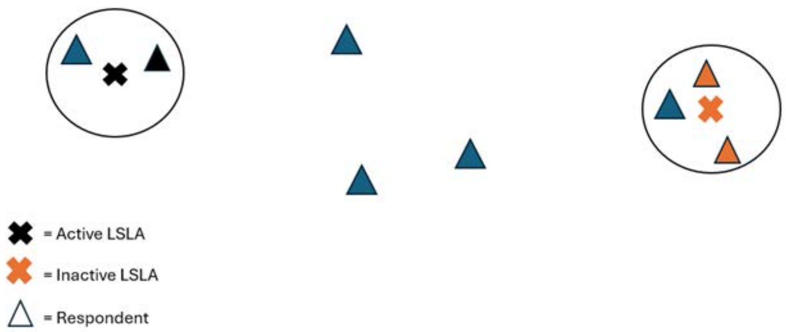
Wegenast et al. (2022) use a 10-kilometer buffer in their geospatial analysis of the impact of LSLAs on trust. I decided to use a 25-kilometer buffer instead for five reasons[4]. First, the Afrobarometer data does not allow for controlling for migration movements, meaning it is unclear whether respondents moved after their schooling or attended school near an LSLA and subsequently relocated. A 25-kilometer buffer helps to address this issue by covering a broader area. Second, LSLAs often cover large areas. The average size of the LSLAs I considered is 27,135.67 hectares, with the largest LSLA being 168,000 hectares. Third, I argued that LSLAs

[4] A 25-kilometer buffer is still rather restrictive. Most researchers use a buffer size of 50 kilometers in geospatial analyses (Wegenast et al., 2022).

lead to income loss through rising local market prices. If a LSLA prevents small-scale farmers in a region from growing crops for local markets, is likely to extend beyond 25 kilometers. Fourth, geocoded data often contain location errors, and larger buffers are more robust against such errors (Knutsen et al., 2017). Lastly, a smaller buffer size would result in too few respondents being affected.

Investors consider various factors when purchasing land, resulting in a non-random distribution of LSLAs in Africa (Wegenast et al., 2022). Since LSLAs may be concentrated in areas with below or above-average education levels, comparing the education of individuals living near LSLAs with those who do not is problematic due to potential selection bias.

Figure 2: Identification Strategy



Note: Created by the author.

To address the selection bias, I modify the identification strategy by Wegenast et al. (2022)[5]. My approach is illustrated in Figure 2. I classify LSLAs into two types: active LSLAs, where the investor actively uses the land, and inactive LSLAs, where the land is purchased by the investor but not used. The assumption behind this is that LSLAs negatively impact the local population only when the land is used by the investors, not when it is purchased but left unused. Consequently, I assume that small-scale farmers retain access to the land until it begins to be utilized. This assumption is justified for two reasons. First, many small-scale farmers already cultivate land with unclear ownership before the LSLA, often remaining unaware of the purchase until production starts (Yengoh et al., 2016). Second, many investors buy land for

[5] My identification strategy builds on the approach developed by Knutsen et al. (2017) and adapted by Wegenast et al. (2022) for LSLAs. I refined it by considering both the age of respondents and their positions within buffers, unlike the other approaches which only consider respondent positions. Moreover, unlike Wegenast et al. (2022), I created buffers around the LSLAs instead of the respondents, as I find this more straightforward. The outcome is the same.

speculation (Dell'Angelo et al., 2017) and have no interest in evicting small-scale farmers, as expulsion incurs costs (Sändig, 2021).

I proceed by dividing the Afrobarometer respondents into three groups: 1) Those within the buffer of an active LSLA and aged 0-16 when land use began, 2) Those within the buffer of an inactive LSLA and aged 0-16 at the time of land purchase, and 3) Those unaffected by any LSLAs during ages 0-16. In Figure 2, one respondent, represented by a black triangle, is within the buffer of an active LSLA and was between 0 and 16 years old when the investor began using the land; hence, he or she belongs to the first group. Another respondent, shown as a blue triangle, is in the same buffer but was 60 years old at the onset of land use, thus is categorized in the reference group, like other respondents outside any LSLA buffer. The same logic applies to the buffer around the inactive LSLA. Two respondents, indicated by orange triangles, are in the buffer and aged 0-16 at the time of purchase, and therefore belong to the second group. The other respondent in the buffer was over 16 at the time of the land purchase and therefore belongs to the third group.

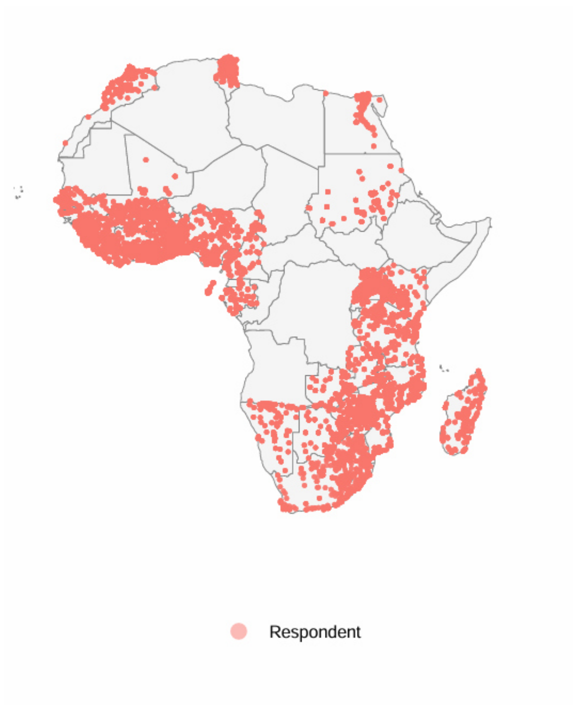
In the subsequent regression analysis, the coefficient of respondents in the buffers of active LSLAs during ages 0 to 16 (β_1) then includes both the selection bias and the impact of LSLAs on education while the coefficient of respondents in the buffer of inactive LSLAs during ages 0 to 16 (β_2) only includes the selection bias. Taking the difference between the coefficients of active and inactive LSLAs $(\beta_1 - \beta_2)$ removes the selection bias. Subsequently, an F-test is conducted to ensure that the difference between the coefficients is statistically significant. This approach is feasible because active and inactive LSLAs are largely similar[6]. The difference is that investors with inactive LSLAs speculate with the land without starting cultivation or are still preparing for production (Wegenast et al., 2022).

Now, I outline the data selection process. Initially, the sixth round of the Afrobarometer includes 52,567 respondents from 36 countries (Afrobarometer, 2016). I removed respondents who aged 0 to 16, were within a 25-kilometer buffer of both inactive and active LSLAs, as it is impossible to determine which LSLA influenced their education. I excluded all respondents from Algeria, Burundi, Cape Verde, Niger, and Mauritius because the Land Matrix

[6] In my case, the median hectare size of active LSLAs is 6774 hectares, while for inactive LSLAs, it is 6474 hectares.

database records no LSLAs in these countries. This accounts for unobserved factors that may make a country unattractive for LSLAs and could influence the characteristics of the group not affected by LSLAs. My final sample includes 46,711 respondents from 31 African countries. 2.36% of the respondents are affected by an active LSLA between the ages of 0 and 16, and 0.24% are affected by an inactive LSLA during this period[7]. Figure 3 displays the locations of the respondents considered.

Figure 3: Locations of Afrobarometer Respondents



Note*: Created by the author.*

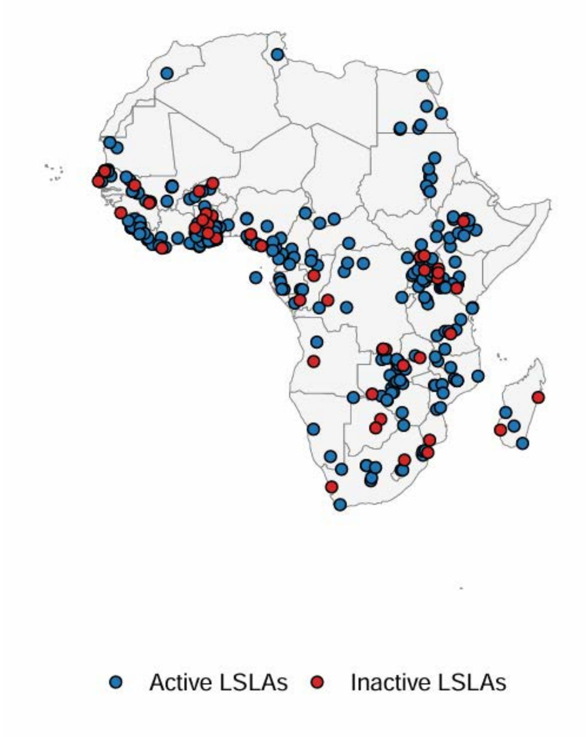
For my analysis, I only include LSLAs with precise coordinates. Despite this, location errors are possible. I consider all LSLAs where the purchase has been completed, regardless of whether the land was bought by a domestic or international investor and irrespective of the post-purchase form of land utilization[8]. I define them as active if the land is used by the investor and inactive if it is not. LSLAs with unclear land use status are excluded. I use the purchase year as the LSLA year since land use typically begins immediately for active LSLAs. If the year

[7] The figures are comparable to Wegenast et al. (2022). Using a 50 km buffer as a robustness check, 6.46% of respondents are affected by active LSLAs (0-16 years old) and 0.76% by inactive LSLAs. These values are higher than those of Wegenast et al. (2022) and the results remain robust (Table C.1).

[8] I do not differentiate because my sample of LSLAs would be too small, resulting in an insufficient number of respondents affected by LSLAs. Forms of post-purchase land utilization include export-oriented agriculture, biofuel production, and renewable energy production (Land Matrix, 2024)

is missing, I manually check the Land Matrix database for the relevant year. LSLAs without any information on the completion year are excluded. Since the sixth round of Afrobarometer surveys began in 2014, I only include LSLAs purchased before 2013. My final sample includes 322 LSLAs in Africa from 1921 to 2013, with 277 being active and 45 inactive. Figure 4 displays the locations of the LSLAs included in the analysis[9].

Figure 4: Locations of LSLAs



Note*: Created by the author.*

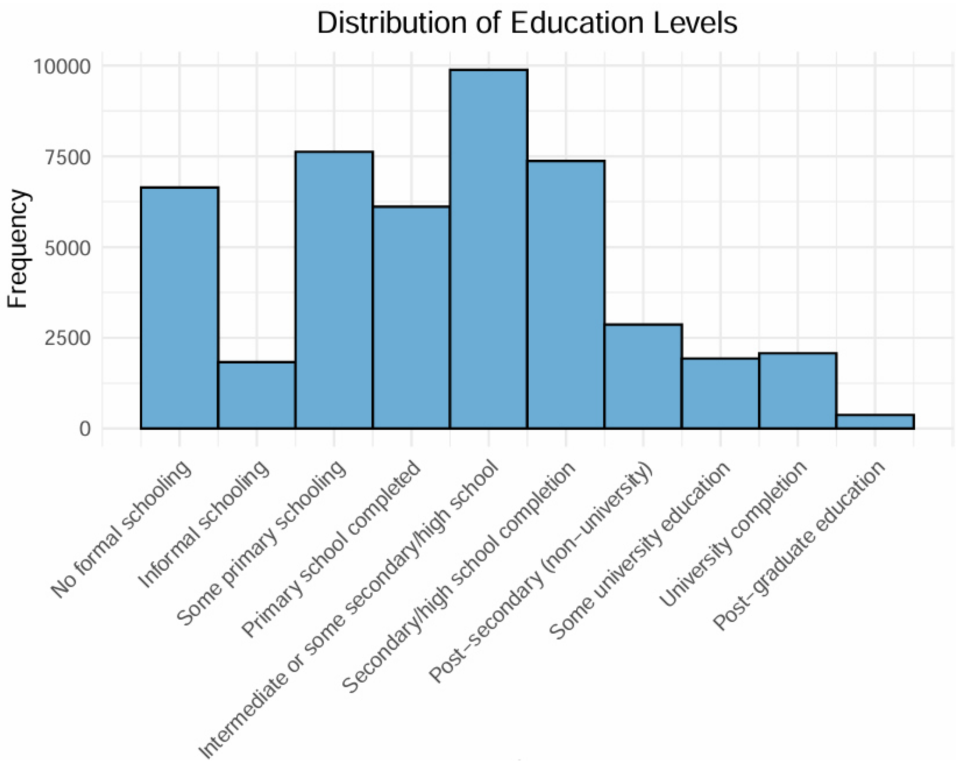
4.2. Operationalization

The dependent variable is *education*, which is measured in the sixth round of Afrobarometer by asking respondents, "What is your highest level of education?" Respondents indicated their education level on a Likert scale, where higher values correspond to higher levels of education. Specifically, 0 indicates no formal schooling, 1 signifies informal schooling (including Koranic schooling), 2 denotes some primary schooling, 3 means primary school completed, 4 represents intermediate or some secondary/high school, 5 indicates secondary/high school completion, 6 refers to post-secondary qualifications other than a university degree (e.g., a diploma from a polytechnic or college), 7 indicates some university education, 8 implies

[9] Appendix A contains a list of all Afrobarometer and Land Matrix countries considered.

university completion, and 9 stands for post-graduate education (Afrobarometer, 2016)[10]. Figure 5 illustrates that the majority of respondents have an education level below secondary education completion.

Figure 5: Histogramm of Education Levels



Note*: Created by the author.*

The independent variable is *active*, indicating whether an individual is affected by an active LSLA between the ages of 0 and 16. *Active* is coded as 1 if an individual is within the buffer of an active LSLA during this age range when land utilization began, and 0 if not.

To investigate the gendered impact of LSLAs on education, I use an interaction term between *active* and *gender*. *Gender* is a dummy variable, with 1 for male respondents and 0 for female respondents.

I control for various confounders. Most variables in the Afrobarometer dataset are post-treatment, meaning their values when respondents were between 0 and 16 years old are unknown. Therefore, I use variables that represent permanent characteristics and do not

[10] I address potential issues with measuring *education* through a Likert scale in Chapter 6.

change over time. Additionally, I utilize control variables from grid data, calculating values for each respondent during the period they were between 0 and 16 years old. Each respondent is matched to their respective grid based on coordinates.

To address the selection bias, I use the variable *inactive*, indicating whether a respondent was affected by an inactive LSLA between the ages of 0 and 16. It takes the value 1 if a respondent is within the buffer of an inactive LSLA during this age range at the time of land purchase, and 0 if not.

To account for differences in the duration respondents are affected by LSLAs, I use the variable *exposure time*. It indicates the number of years between ages 0 and 16 that a respondent is affected by an active or inactive LSLA. For the reference category, this value is always 0. This variable is particularly useful as it also captures the age at which each respondent was affected by the LSLA. For instance, if the variable takes the value 5, it means the respondent was 11 years old when the land was purchased or when the utilization of the purchased land began.

I use gender, religion, and age dummy variables as control variables from the Afrobarometer dataset. Men generally have better access to education and are more likely to hold jobs created by LSLAs, making them more likely to live near LSLA locations (Björkman-Nyqvist, 2013; Yengoh & Armah, 2015). *Gender* is operationalized as in the interaction term. *Religion* is coded as 1 if the respondent belongs to any Muslim, Sunni, Ismaeli, Mouridiya, Tijaniya, Qadiriya, Shia, or traditional/ethnic religion; otherwise, it is 0. These religious groups often have poorer access to education, and women in these groups frequently face educational barriers (Alesina et al., 2023). Age dummies are used to account for differences in access to education between younger and older individuals, and to control for the timing of the period when respondents were between 0 to 16 years old, as access to education has improved over time (Brown et al., 2023). Each respondent is coded with a 1 for the age group they belong to and 0 for all other groups. The age groups are 18-25, 26-35, 36-45, 46-55, 56-65, and 66+, with 46-55 serving as the reference category.

Respondents in areas with good agricultural conditions are more likely to be affected by LSLAs (D'Odorico et al., 2017) and potentially have higher incomes, allowing for greater educational investment. To control for agricultural conditions, I use two variables. First, I utilize data from the gridded dataset by Schneider et al. (2015), which provides yearly precipitation measurements in millimeters for each grid, derived from monthly meteorological statistics compiled by the Global Precipitation Climatology from 1946 to 2013. To operationalize *rain*, I calculated the average precipitation in each respondent's grid for the period when the respondent was between 0 and 16 years old. Additionally, I control for the agricultural land available to the respondent and LSLA investors using the dataset by Meiyappan et al. (2012). This dataset reports the percentage of a grid's area covered by agricultural land from 1950 to 2010. To operationalize *agricultural land*, I calculated the average percentage of agricultural land in each respondent's grid for the period when the respondent was between 0 and 16 years old[11].

To control for other agricultural shocks that might negatively impact a respondent's education, I utilize drought data from Beguería et al. (2010). They measure drought intensity by calculating, for each grid and year, the proportion of months within the growing season with values below -1.5 in the Standardized Precipitation and Evapotranspiration Index (SPEI-1). The growing season is defined as the months when the main crop of each grid is cultivated, with values below -1.5 indicating severe drought conditions. To operationalize *drought*, I calculated the average number of months with SPEI-1 values below -1.5 during the growing season for each respondent's grid when they were between 0 and 16 years old.

Access to education is often better in urban areas (Björkman-Nyqvist, 2013). To account for this, I use the control variable *urban*, which I operationalize by calculating the average percentage of each respondent's grid covered by urban areas in the time the respondent was between 0 and 16 years old. The data for this come from Meiyappan et al. (2022). Descriptive statistics of the variables are shown in Table 1.[12].

[11] I sourced the descriptions of the datasets for the grid-based variables from the PRIO-GRID Codebook, citing them as instructed (see Tollefsen et al., 2012).

[12] Missing observations for both Afrobarometer variables and grid-based control variables were coded as NAs. The number of observations considered for calculating grid-based variables may vary from respondent to respondent.

Table 1: Descriptive Statistics

Variable	N	Mean	SD	Min	Max
Education	46710	3.478	2.197	0	9
Active	46711	0.024	0.152	0	1
Inactive	46711	0.002	0.049	0	1
Gender	46710	0.495	0.5	0	1
Religion	46711	0.29	0.454	0	1
Urban	44868	0.563	1.192	0	19.865
Drought	43456	0.05	0.025	0	0.6
Rain	46294	588.667	303.049	0.321	1082.364
Agricultural Land	44868	33.196	16.035	0	99.03
Exposure Time	46468	0.103	0.942	0	16
Age (18 -25)	46431	0.245	0.43	0	1
Age (26-35)	46431	0.304	0.46	0	1
Age (36-45)	46431	0.204	0.403	0	1
Age (46-55)	46431	0.125	0.331	0	1
Age (56-65)	46431	0.074	0.262	0	1
Age (66 +)	46431	0.049	0.216	0	1

4.3. Model Specification

I use model 1 to test my first hypothesis. For hypothesis 2, I employ two distinct approaches: First, model 2 incorporates an interaction term between *active* and *gender*. Second, following Wegenast et al. (2022), I apply model 1 without using *gender* as a control variable on gender-segregated datasets. This allows me to remove the selection bias, which is not possible with the interaction term. I employ OLS regressions with region fixed effects to address time-invariant regional characteristics that may affect respondent education. Additionally, I utilize heteroskedasticity-robust standard errors. Below, my regression models are presented.

Model 1: $Education_{T(S)ilr} = \beta_0 + \beta_1 Active_{T(0-16)ilr} + \beta_2 Inactive_{T\,(0-16)ilr} + X_{T(S)ilr}\theta_X + Z_{T(0-16)ilr}\theta_Z + rf_r + \varepsilon_{T(S)ilr}$

In model 1, $Education_{T(S)ilr}$ represents the education level of individual i in locality l, region r and the time of the survey $T(S)$. $\beta_1 Active_{T\,(0-16)ilr}$ indicates whether individual i is within the buffer of an active LSLA in locality l and region r within the time period $T(0-16)$, when the respondent was between 0 and 16 years old. $\beta_2 Inactive_{T\,(0-16)ilr}$ indicates whether individual i is within the buffer zone of an inactive LSLA in locality l and region r within the time period $T(0-16)$. $X_{T(S)ilr}$ is a vector of all constant individual-level control variables measured at the time of each survey, and θ_X is the vector of corresponding coefficients. $Z_{T(0-16)ilr}$ is a vector of all grid-based control variables specific to the period when the respondent was aged between 0 and 16, and θ_Z contains the corresponding coefficients. rf_r represents the region fixed effects, and $\varepsilon_{T(S)ilr}$ is the error term.

Model 2: $Education_{T(S)ilr} = \beta_0 + \beta_1 Active_{T(0-16)ilr} + \beta_2 Inactive_{T\,(0-16)ilr} + \beta_3 Gender_{T(S)ilr} + \beta_4 \left(Active_{T(0-16)lr}\ x\ Gender_{ilr}\right) + X_{T(S)ilr}\theta_X + Z_{T(0-16)ilr}\theta_Z + rf_r + \varepsilon_{T(S)ilr}$

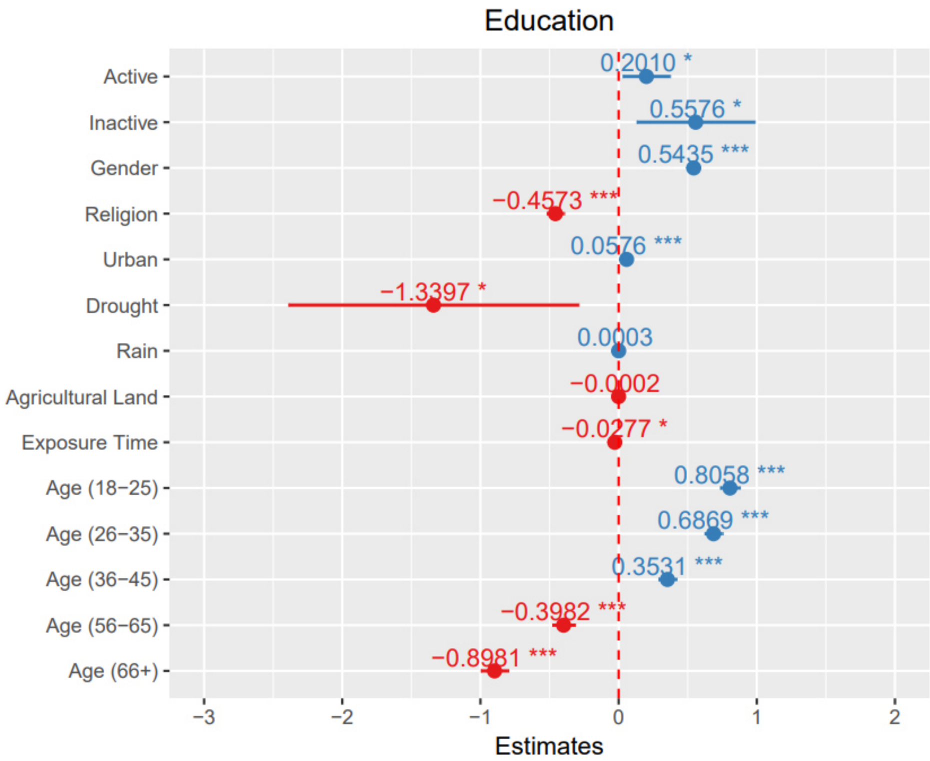
Model 2 differs from Model 1 insofar as I have included the interaction term $\beta_4 \left(Active_{T\,(0-16)ilr}\ x\ Gender_{T(S)ilr}\right)$.

5. Results

I focus initially on testing hypothesis 1 and then proceed to hypothesis 2. I do not reject hypothesis 1 if the difference between *active* and *inactive* $(\beta_1 - \beta_2)$ results in a negative value, both coefficients are statistically significant, and the difference between the two coefficients is statistically significant. Hypothesis 2 is supported if the interaction term is statistically significant and goes in the expected direction, and the difference between *active* and *inactive* yields a larger negative value for men in the gender-differentiated data sets. As with hypothesis 1, both the individual coefficients and their difference must be statistically significant.

Figure 6 shows the results of the regression analysis. The coefficients of *active* and *inactive* are statistically significant ($p < 0.05$) and the difference between the two coefficients yields a negative value of – 0.36. To test whether the difference between *active* and *inactive* is statistically significant, I conducted an F-test to examine whether I can reject the null hypothesis that *active* and *inactive* are similar $(\beta_1 - \beta_2 = 0)$. The result ($F = 2.71$, $p < 0.1$) indicates that the difference is statistically significant (see Regression Table in Appendix B.1). Thus, I can confirm hypothesis 1.

Figure 6: Regression Results

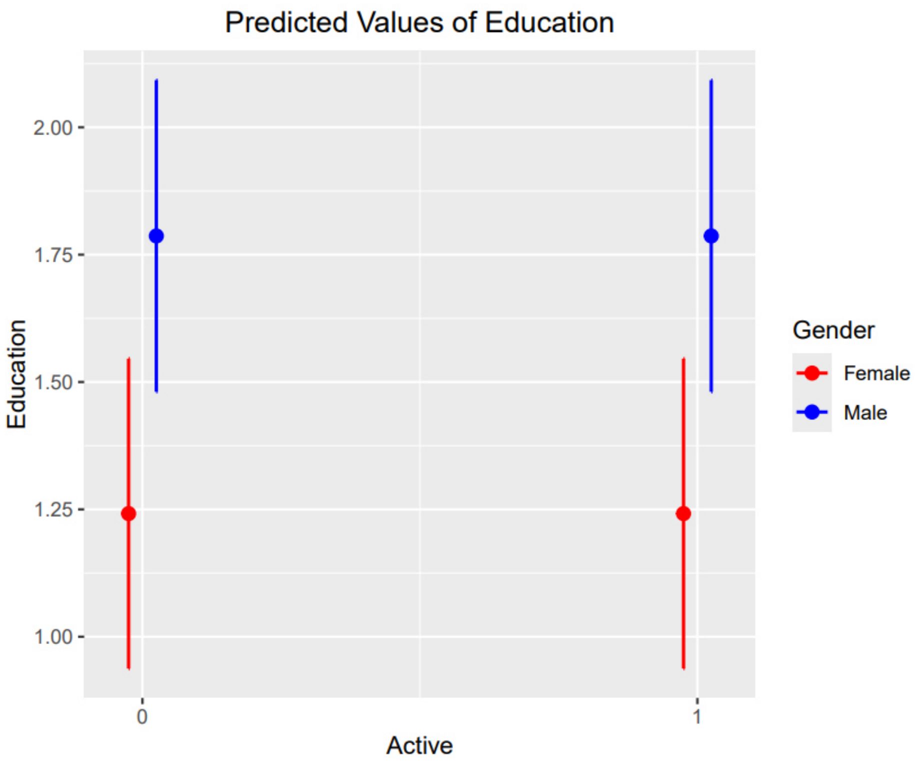


*Note: * p < 0.05, ** p < 0.01, *** p < 0.001. Robust standard errors are clustered by region. Negative coefficients are in red, positive coefficients in blue, with 95% confidence intervals shown. Regional fixed effects are applied. The reference group for active and inactive is respondents not affected by any LSLA during ages 0 to 16. For other dummy variables, the reference group is those with a value of 0. The reference group for age dummies is 46-55. Regressions were estimated using the Fixest package in R, which does not report an intercept by default.*

Regarding the control variables, it is noteworthy that *drought* has a substantive statistically significant negative impact on education ($p < 0.05$), aligning with the existing literature. Additionally, *exposure time* has a statistically significant negative impact on education ($p < 0.05$). *Gender* ($p < 0.001$), *religion* ($p < 0.001$), *urban* ($p < 0.001$), and the age dummies ($p < 0.001$) also have statistically significant effects on education in the expected direction.

I now present the results of the analysis on the gendered impacts of LSLAs on education. The interaction term between *active* and *gender* is not statistically significant (see Regression Table in Appendix B.2.). Figure 7 illustrates the marginal effects of the interaction. The predicted education value for males does not decrease, as expected, when *active* switches from 0 to 1.

Figure 7: Marginal Effects of Interaction Term



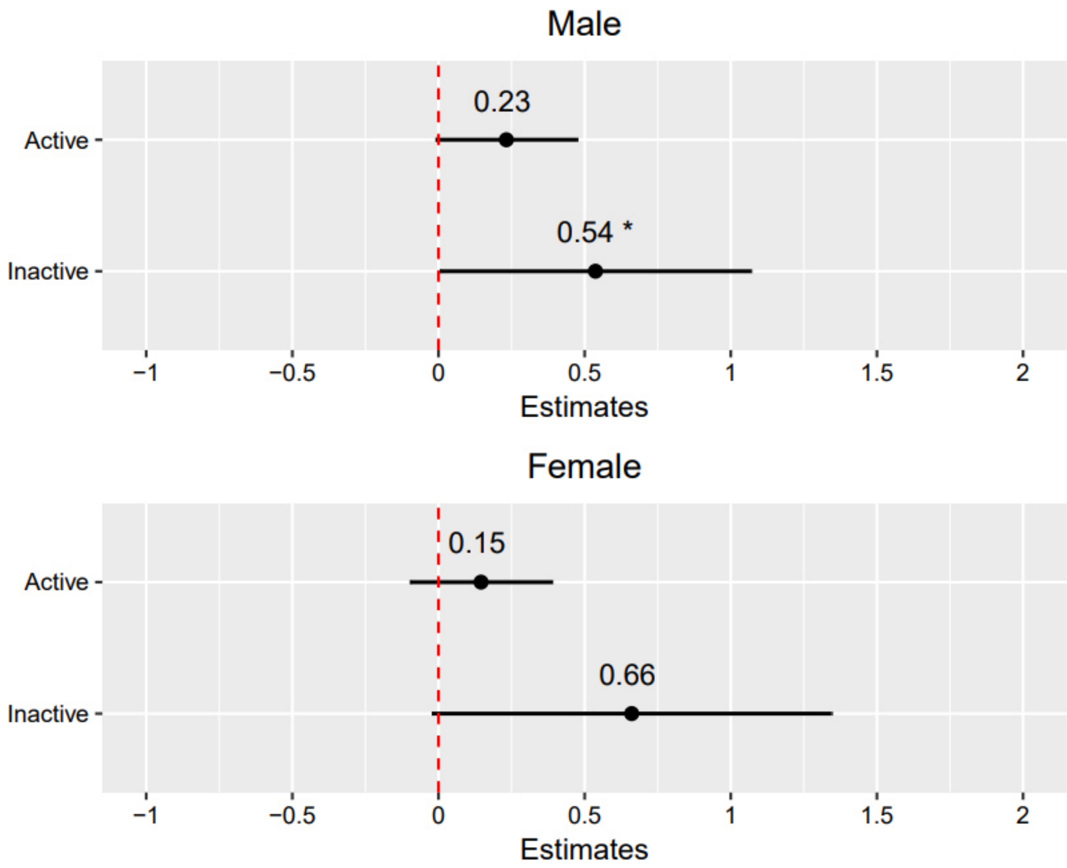
Note: All other variables are held constant at their means. The bars around the coefficients represent the 95% confidence intervals.

The interaction term does not account for selection bias, so I separated the dataset by gender to examine whether the difference between *active* and *inactive* yields a larger negative value for the male dataset.

I checked whether being affected by an LSLA is influenced by gender. 2.72% of women and 2.48% of men are affected by an inactive or active LSLA during the ages 0 to 16. Despite the small difference, the results should be interpreted with caution.

Figure 8 shows that, contrary to my expectations, active LSLAs have a larger negative impact on females (see Regression Table in Appendix B. 3). The difference between coefficients is not statistically significant in either dataset.

Figure 8: Regression Analysis (Gender Differentiated)



*Note: * p < 0.05, ** p < 0.01, *** p < 0.001. The models include all control variables except gender. The coefficients are presented with 95% confidence intervals. The model includes regional fixed effects and robust standard errors clustered by region.*

Since the interaction term is not statistically significant, and the difference between active and inactive does not yield a larger negative value for males compared to females, I reject hypothesis 2.

6. Robustness Checks and Causal Mechanisms Testing

I conducted various robustness checks (see Appendix C) and subsequently highlight a few key findings. I tested hypothesis 1 using a buffer size of 50 Kilometers (Table C.1). *Active* (*p < 0.1)* and *inactive (p < 0.001)* are statistically significant. The difference yields a negative value of – 0.38 and is statistically significant (F = 9.04, p < 0.01). Moreover, I replaced *religion* with *ethnicity* to address that religion, in some cases, might be a post-treatment variable too. My results remain robust (Table C.10). Both *active* (*p < 0.1)* and *inactive* (p < 0.01) are statistically significant. Taking the difference yields a negative value of – 0.4 and the difference is statistically significant (F = 3.39, $p < 0.1$).

Additionally, I operationalized the dependent variable *education* by creating binary variables for different educational stages and conducted logit regressions. This approach addresses the issue of running OLS regressions on ordered outcomes, which could violate the assumption of independent error terms (Wegenast et al., 2022), and accounts for respondents under 30 who may not have completed their education. The coefficient differences usually trend as expected: LSLAs increase the likelihood of having only primary education and decrease the likelihood of having secondary education. However, the coefficients are not statistically significant in most models, and their differences are not significant in any of the models (Tables C.4 & C.7).

The interaction term is not significant in almost all logit models and does not follow the expected direction. Although *active* and *inactive* are not statistically significant in most models, the analysis based on gender-separated datasets suggests that LSLAs have a stronger negative impact on males' education (Tables C.2,C.3,C.5,C.6,C.8,C.9,C.11,C.12).

I also tested my theory by examining four conditions: LSLAs increase food insecurity, reduce income, that reduced income and food insecurity negatively impact education, and that LSLAs do not have a negative impact on school infrastructure. The results are mixed. LSLAs improve school infrastructure, allowing me to rule out that the negative impact on education is due to a deterioration of the education supply side. However, LSLAs do not have a statistically significant effect on income or food insecurity, although the coefficient difference points in the expected direction. Nonetheless, the impact of food insecurity and income loss on education is statistically significant and negative (see Appendix D for analysis and discussion).

7. Discussion

The analysis indicates that LSLAs have a negative effect on education, with no evidence that this effect is more pronounced for men. The results remain robust when increasing the buffer size and the negative impact of LSLAs on education is not due to a deterioration of school infrastructure. However, the F-test in main the analysis is only significant at the 10% level and the difference between *active* and *inactive* is no longer significant when using logit models. Given the mixed results from robustness checks and causal mechanisms testing, the findings should be interpreted with caution. Additionally, there are several limitations to my analysis, which I will outline next.

My research design does not control for migration movements, implying I cannot determine if respondents lived near the LSLA during the period when they were between 0 and 16 years old or if they moved there later. Although most respondents are young, so the time when they were between 0 and 16 is relatively close to the survey date, and I used a 25-kilometer buffer to account for migration, it remains a significant limitation.

Using grid-based variables is another limitation, as local conditions within grids can vary. However, grid-based variables are more suitable than other Afrobarometer control variables, which are almost certainly post-treatment variables.

Less than a third of the LSLAs I analyzed are inactive, yet in reality, inactive LSLAs greatly outnumber active ones as land speculation is a major incentive for investors (Dell'Angelo et al., 2017). Therefore, the proportion of people affected by inactive LSLAs is likely underestimated in my analysis. Capturing inactive LSLAs is challenging because investors often avoid public scrutiny (Land Matrix, 2024).

Using the Afrobarometer dataset also has limitations. Only 36 African countries were included in the sixth round, with disproportionate representation of West and East Africa, limiting the external validity of my results. External validity is a broader issue in LSLA literature. Africa represents an extreme case. While LSLAs also have significant negative impacts on communities in Latin America and Asia (Dell'Angelo et al., 2021), a smaller proportion of people in these regions depend on agriculture (Davis et al., 2023). Additionally, investors buy more land there, which was already used for export-oriented agriculture compared to Africa (Müller et al., 2021). Moreover, the external validity of theories, including mine, regarding the gendered impact of LSLAs is constrained by significant variations in gender perceptions across and within regions, making these theories rather educated guesses than definitive conclusions.

My analysis highlights a terminological issue in the LSLA literature. Wegenast et al. (2022) and I have investigated the impact of actively used LSLAs on the local population. This means that the impact on the local population is not due to the land purchase itself, but rather the utilization of the land after the purchase. This distinction needs to be made clear in the literature. Additionally, this leads to a controversial hypothesis that warrants further investigation: land speculation is not as problematic as land utilization because farmers do not lose access to the land.

Despite its limitations, this paper contributes to the literature on agricultural shocks and the socioeconomic effects of LSLAs. It argues for recognizing LSLAs as agricultural shocks, expanding the focus beyond those caused by weather or market price fluctuations. It also introduces education as a critical socioeconomic indicator affected by LSLAs, which has not been previously examined.

The findings have significant policy implications. LSLAs, often promoted by African governments as catalysts for agricultural modernization and development in impoverished rural areas (Wegenast et al., 2022), negatively impact education. This can trap individuals in poverty by leaving them without the qualifications needed for modern agribusiness jobs, further impoverishing rural regions. Governments should ensure sustainable land use by investors. Policies requiring the employment of small-scale farmers who previously cultivated the land and providing these farmers with official land titles would protect them from unexpected LSLAs and improve their negotiation positions with investors.

8. Conclusion

The aim of this paper was to answer the research question: What is the impact of LSLAs on education? I argued that LSLAs negatively affect education by increasing food insecurity and reducing income, leaving households with fewer resources for education and forcing them to withdraw children from school to generate additional income. I also argued that the negative effect is more pronounced for boys, as they can contribute more to household income and are thus more likely to be taken out of school.

To test the hypotheses, I used a geospatial research design. The regression results indicate that being affected by LSLAs between the ages of 0 and 16 has a statistically significant negative impact on education. I found no evidence that this negative effect is stronger for boys.

There are many avenues for future research, such as differentiating LSLAs by international and domestic investors and different land uses. LSLAs have far-reaching environmental impacts, including soil degradation and reduced biodiversity (D'Odorico et al., 2017). This potentially makes smallholders more vulnerable to other agricultural shocks. Future research should therefore investigate how LSLAs and other agricultural shocks interact. Moreover, integrating institutional variables into research on agricultural shocks and education is promising, as the impact of these shocks on education may be moderated by factors such as local institutional quality. Research on LSLAs should expand beyond Africa. Since the proportion of people dependent on agricultural income is lower in Asia and Latin America, it is important to focus on vulnerable groups, particularly indigenous populations, in these regions.

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Appendix

Appendix A: Countries Included in the Analysis

Afrobarometer: Benin, Botswana, Burkina Faso, Cameroon, Cote d'Ivoire, Egypt, Gabon, Ghana, Guinea, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Morocco, Mozambique, Namibia, Nigeria, São Tomé and Príncipe, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe.

Land Matrix: Angola, Benin, Côte d'Ivoire, Cameroon, Rep. of Congo, Egypt, Ethiopia, Ghana, Guinea, Kenya, Liberia, Madagascar, Mali, Mozambique, Namibia, Nigeria, Sudan, South Sudan, Senegal, Sierra Leone, Swaziland, Togo, Tanzania, Uganda, Dem. Rep. Congo, Zambia, Gabon, Central African Republic, Chad, Zimbabwe, Malawi, São Tomé and Principe, Mauritania, Lesotho, Burkina Faso, Morocco, Botswana, South Africa, Tunisia

Appendix B: Regression Results

Note: By default, the *fixest* package does not report intercepts. Standard errors are clustered by region in all models, including those in the robustness checks and causal mechanism testing. In order to safe space, I do not provide the results of the F-tests in the appendix if any of these conditions apply: Both *active* and *inactive* are not statistically significant, or the difference between *active* and *inactive* is not significant. Exceptions where these conditions do not apply are addressed in the main text and appendix, along with the corresponding F-test results. I do not provide F-tests for the interaction models, as the focus there is on the interaction term between *active* and *gender*. I would provide them for the gender-differentiated data sets. However, in all cases, either one of the coefficients is not significant or the F-test result is not significant.

Table B.1: Regression Results

	Education
Active	0.2010*
	(0.0870)
Inactive	0.5576*
	(0.2176)
Gender	0.5435***
	(0.0173)
Religion	-0.4573***
	(0.0318)
Urban	0.0576***
	(0.0160)
Drought	-1.3397*
	(0.5352)
Rain	0.0003
	(0.0003)
Agricultural Land	-0.0002
	(0.0015)
Exposure Time	-0.0277*
	(0.0126)
Age (18 - 25)	0.8058***
	(0.0362)
Age (26 - 35)	0.6869***
	(0.0331)
Age (36 - 45)	0.3531***
	(0.0333)
Age (56 - 65)	-0.3982***
	(0.0419)
Age (66 +)	-0.8981***
	(0.0503)
Num.Obs.	43102
R2	0.315
R2 Adj.	0.308
AIC	172897.6
BIC	176452.8
RMSE	1.78
Std.Errors	Heteroskedasticity-robust
FE: region	Yes

- + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2. : Regression Results (Interaction)

	Education
Active	0.2395*
	(0.1002)
Inactive	0.5578*
	(0.2176)
Gender	0.5450***
	(0.0175)
Religion	-0.4573***
	(0.0318)
Urban	0.0576***
	(0.0160)
Drought	-1.3381*
	(0.5352)
Rain	0.0003
	(0.0003)
Agricultural Land	-0.0002
	(0.0015)
Exposure Time	-0.0278*
	(0.0125)
Age (18 - 25)	0.8059***
	(0.0362)
Age (26 - 35)	0.6869***
	(0.0331)
Age (36 – 45)	0.3531***
	(0.0333)
Age 56 - 65)	-0.3983***
	(0.0419)
Age (66 +)	-0.8983***
	(0.0503)
Active × Gender	-0.0806
	(0.1104)
Num.Obs.	43102
R2	0.315
R2 Adj.	0.308
AIC	172899.2
BIC	176463.1
RMSE	1.78
Std.Errors	Heteroskedasticity-robust
FE: region	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

F – Test: F = 2.71, p < 0.1

Table B.3. : Regression Results (Gender Differentiated)

	(Male) **Education**	(Female) **Education**
Active	0.2321+	0.1455
	(0.1235)	(0.1239)
Inactive	0.5371*	0.6609+
	(0.2714)	(0.3487)
Religion	-0.4729***	-0.4705***
	(0.0453)	(0.0444)
Urban	0.0480*	0.0666**
	(0.0232)	(0.0219)
Drought	-1.4541+	-0.9296
	(0.7596)	(0.7553)
Rain	0.0000	0.0004
	(0.0004)	(0.0004)
Agricultural Land	-0.0005	0.0005
	(0.0021)	(0.0021)
Exposure Time	-0.0267+	-0.0279
	(0.0157)	(0.0195)
Age (18 - 25)	0.6888***	0.9571***
	(0.0526)	(0.0500)
Age (26 - 35)	0.5969***	0.7922***
	(0.0481)	(0.0455)
Age (36 - 45)	0.3179***	0.4044***
	(0.0479)	(0.0464)
Age (56 - 65)	-0.3273***	-0.5329***
	(0.0578)	(0.0605)
Age (66 +)	-0.8586***	-1.0558***
	(0.0673)	(0.0763)
Num.Obs.	21352	21750
R2	0.290	0.353
R2 Adj.	0.276	0.341
AIC	86408.3	86279.5
BIC	89667.5	89546.3
RMSE	1.80	1.73
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes

- + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix C: Robustness Checks

Note: I also report the models with a 10 km buffer. However, my confidence in the 10 km buffer is limited, as only 0.39% of respondents are coded as *active* and 0.08% as *inactive* at this buffer size.

Primary Education and *Secondary Education* are binary variables. *Primary Education* is coded as 1 if the respondent indicates having some primary schooling or having completed primary schooling, and 0 otherwise. *Secondary Education* is coded as 1 if the respondent reports attending intermediate school, some secondary school/high school, having completed secondary school/high school, or having post-secondary qualifications other than a university degree, such as a diploma from a polytechnic or college, and 0 otherwise.

Table C.1 : Comparative Regression Results

	(10 km)	(25 km)	(50 km)
	Education	**Education**	**Education**
Active	0.4122+	0.2010*	0.0758+
	(0.2142)	(0.0870)	(0.0432)
Inactive	0.5184	0.5576*	0.4438***
	(0.3287)	(0.2176)	(0.1198)
Gender	0.5435***	0.5435***	0.5433***
	(0.0173)	(0.0173)	(0.0173)
Religion	-0.4520***	-0.4573***	-0.4549***
	(0.0317)	(0.0318)	(0.0317)
Urban	0.0585***	0.0576***	0.0584***
	(0.0157)	(0.0160)	(0.0157)
Drought	-1.3518*	-1.3397*	-1.2929*
	(0.5338)	(0.5352)	(0.5343)
Rain	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)
Agri. Land	-0.0001	-0.0002	-0.0003
	(0.0015)	(0.0015)	(0.0015)
Exp. Time	-0.0123	-0.0277*	-0.0082
	(0.0294)	(0.0126)	(0.0075)
Age (18 - 25)	0.8103***	0.8058***	0.7976***
	(0.0359)	(0.0362)	(0.0364)
Age (26 - 35)	0.6882***	0.6869***	0.6834***
	(0.0330)	(0.0331)	(0.0331)
Age (36 - 45)	0.3541***	0.3531***	0.3523***
	(0.0333)	(0.0333)	(0.0333)
Age (56 – 65)	-0.3974***	-0.3982***	-0.3975***
	(0.0419)	(0.0419)	(0.0419)
Age (66 +)	-0.8975***	-0.8981***	-0.8983***
	(0.0503)	(0.0503)	(0.0503)
Num.Obs.	43317	43102	43232
R2	0.314	0.315	0.314
R2 Adj.	0.307	0.308	0.308
AIC	173718.4	172897.6	173400.1
BIC	177275.7	176452.8	176956.6
RMSE	1.78	1.78	1.78
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

F – Test (25 km): F = 2.71, p < 0.1

F – Test (50 km): F = 9.04, p < 0.01

Table C.2 : Comparative Regression Results (Interaction)

	(10 km)	(25 km)	(50 km)
	Education	**Education**	**Education**
Active	0.5198*	0.2395*	0.0615
	(0.2341)	(0.1002)	(0.0528)
Inactive	0.5123	0.5578*	0.4439***
	(0.3294)	(0.2176)	(0.1198)
Gender	0.5444***	0.5450***	0.5413***
	(0.0173)	(0.0175)	(0.0180)
Religion	-0.4520***	-0.4573***	-0.4549***
	(0.0317)	(0.0318)	(0.0317)
Urban	0.0585***	0.0576***	0.0583***
	(0.0157)	(0.0160)	(0.0157)
Drought	-1.3523*	-1.3381*	-1.2954*
	(0.5339)	(0.5352)	(0.5344)
Rain	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)
Agri. Land	-0.0001	-0.0002	-0.0003
	(0.0015)	(0.0015)	(0.0015)
Exp. Time	-0.0108	-0.0278*	-0.0082
	(0.0297)	(0.0125)	(0.0075)
Age (18 - 25)	0.8102***	0.8059***	0.7976***
	(0.0359)	(0.0362)	(0.0364)
Age (26 -35)	0.6883***	0.6869***	0.6834***
	(0.0330)	(0.0331)	(0.0331)
Age (36 - 45)	0.3541***	0.3531***	0.3524***
	(0.0333)	(0.0333)	(0.0333)
Age (56 - 65)	-0.3975***	-0.3983***	-0.3973***
	(0.0419)	(0.0419)	(0.0419)
Age (66 +)	-0.8977***	-0.8983***	-0.8980***
	(0.0503)	(0.0503)	(0.0503)
Active × Gender	-0.2530	-0.0806	0.0305
	(0.2631)	(0.1104)	(0.0629)
Num.Obs.	43317	43102	43232
R2	0.314	0.315	0.314
R2 Adj.	0.307	0.308	0.308
AIC	173719.6	172899.2	173401.9
BIC	177285.5	176463.1	176967.1
RMSE	1.78	1.78	1.78
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table C.3 : Comparative Regression Results (Gender Differentiated)

	(M: 10 km) **Education**	(M:25 km) **Education**	(M: 50 km) **Education**	(F: 10 km) **Education**	(F: 25 km) **Education**	(F: 50 km) **Education**
Active	0.4633	0.2321+	0.1240*	0.3437	0.1455	0.0273
	(0.3447)	(0.1235)	(0.0613)	(0.2722)	(0.1239)	(0.0606)
Inactive	0.6516	0.5371*	0.2247	0.5338	0.6609+	0.6201***
	(0.4507)	(0.2714)	(0.1605)	(0.4793)	(0.3487)	(0.1747)
Religion	-0.4701***	-0.4729***	-0.4733***	-0.4628***	-0.4705***	-0.4647***
	(0.0452)	(0.0453)	(0.0452)	(0.0444)	(0.0444)	(0.0445)
Urban	0.0497*	0.0480*	0.0481*	0.0674**	0.0666**	0.0683**
	(0.0228)	(0.0232)	(0.0229)	(0.0214)	(0.0219)	(0.0214)
Drought	-1.4469+	-1.4541+	-1.4228+	-0.9636	-0.9296	-0.8624
	(0.7577)	(0.7596)	(0.7593)	(0.7532)	(0.7553)	(0.7533)
Rain	0.0000	0.0000	-0.0001	0.0003	0.0004	0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Agri. Land	-0.0006	-0.0005	-0.0007	0.0007	0.0005	0.0004
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Exp. Time	-0.0367	-0.0267+	-0.0091	0.0137	-0.0279	-0.0072
	(0.0419)	(0.0157)	(0.0102)	(0.0418)	(0.0195)	(0.0110)
Age (18-26)	0.6917***	0.6888***	0.6780***	0.9608***	0.9571***	0.9521***
	(0.0522)	(0.0526)	(0.0529)	(0.0496)	(0.0500)	(0.0503)
Age (26 - 35)	0.5991***	0.5969***	0.5941***	0.7913***	0.7922***	0.7873***
	(0.0480)	(0.0481)	(0.0481)	(0.0454)	(0.0455)	(0.0455)
Age (36 - 45)	0.3193***	0.3179***	0.3180***	0.4047***	0.4044***	0.4028***
	(0.0478)	(0.0479)	(0.0478)	(0.0464)	(0.0464)	(0.0464)
Age (46 -55)	-0.3268***	-0.3273***	-0.3263***	-0.5320***	-0.5329***	-0.5329***
	(0.0578)	(0.0578)	(0.0578)	(0.0605)	(0.0605)	(0.0605)
Age (66+)	-0.8590***	-0.8586***	-0.8577***	-1.0540***	-1.0558***	-1.0570***
	(0.0672)	(0.0673)	(0.0673)	(0.0762)	(0.0763)	(0.0763)
Num.Obs.	21448	21352	21410	21869	21750	21822
R2	0.290	0.290	0.290	0.352	0.353	0.353
R2 Adj.	0.276	0.276	0.276	0.340	0.341	0.341
AIC	86767.0	86408.3	86635.0	86741.3	86279.5	86549.4
BIC	90028.1	89667.5	89895.4	90010.4	89546.3	89817.6
RMSE	1.79	1.80	1.80	1.73	1.73	1.73
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. M = Male. F = Female.

Table C.4 : Logit Regression Results Primary Education

	(10 km)	(25 km)	(50 km)
	Primary Education	**Primary Education**	**Primary Education**
Active	-0.5071	-0.2166	-0.1394*
	(0.3144)	(0.1336)	(0.0613)
Inactive	-0.7201	-0.6438	-0.1636
	(0.5853)	(0.4091)	(0.1615)
Gender	-0.2411***	-0.2383***	-0.2392***
	(0.0231)	(0.0231)	(0.0231)
Religion	0.0557	0.0556	0.0549
	(0.0412)	(0.0413)	(0.0413)
Urban	-0.0465+	-0.0432+	-0.0464+
	(0.0237)	(0.0240)	(0.0238)
Drought	0.9941	1.0370	1.0317
	(0.7191)	(0.7211)	(0.7193)
Rain	-0.0025***	-0.0024***	-0.0025***
	(0.0004)	(0.0004)	(0.0004)
Agri. Land	0.0016	0.0016	0.0017
	(0.0019)	(0.0019)	(0.0019)
Exp. Time	0.0290	0.0219	0.0007
	(0.0411)	(0.0189)	(0.0111)
Age (18 - 25)	-0.5358***	-0.5352***	-0.5149***
	(0.0482)	(0.0485)	(0.0489)
Age (26 - 35)	-0.3207***	-0.3233***	-0.3140***
	(0.0419)	(0.0420)	(0.0420)
Age (36 - 45)	-0.2149***	-0.2125***	-0.2136***
	(0.0421)	(0.0421)	(0.0421)
Age (56 - 55)	0.1011+	0.1007+	0.1001+
	(0.0527)	(0.0527)	(0.0527)
Age (66 +)	0.0303	0.0301	0.0288
	(0.0648)	(0.0648)	(0.0648)
Num.Obs.	43195	42980	43110
R2	0.130	0.130	0.130
R2 Adj.	0.115	0.115	0.115
AIC	46834.6	46616.5	46753.8
BIC	50338.7	50118.6	50257.1
RMSE	0.42	0.42	0.42
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table C. 5: Logit Regression Results Primary Education (Interaction)

	(10 km)	(25 km)	(50 km)
	Primary Education	**Primary Education**	**Primary Education**
Active	-0.4635	-0.1360	-0.0270
	(0.3493)	(0.1501)	(0.0735)
Inactive	-0.7216	-0.6433	-0.1632
	(0.5858)	(0.4093)	(0.1616)
Gender	-0.2408***	-0.2350***	-0.2232***
	(0.0231)	(0.0234)	(0.0239)
Religion	0.0556	0.0557	0.0550
	(0.0412)	(0.0413)	(0.0413)
Urban	-0.0465+	-0.0431+	-0.0459+
	(0.0237)	(0.0240)	(0.0238)
Drought	0.9937	1.0403	1.0506
	(0.7191)	(0.7212)	(0.7194)
Rain	-0.0025***	-0.0024***	-0.0024***
	(0.0004)	(0.0004)	(0.0004)
Agri. Land	0.0016	0.0016	0.0017
	(0.0019)	(0.0019)	(0.0019)
Exp. Time	0.0293	0.0216	0.0005
	(0.0413)	(0.0190)	(0.0112)
Age (18 - 26)	-0.5359***	-0.5351***	-0.5148***
	(0.0482)	(0.0485)	(0.0489)
Age (26 - 35)	-0.3207***	-0.3232***	-0.3140***
	(0.0419)	(0.0420)	(0.0420)
Age (36 - 45)	-0.2149***	-0.2125***	-0.2138***
	(0.0421)	(0.0421)	(0.0421)
Age (56 - 65)	0.1011+	0.1005+	0.0993+
	(0.0527)	(0.0527)	(0.0527)
Age (66+)	0.0302	0.0296	0.0269
	(0.0648)	(0.0648)	(0.0648)
Active × Gender	-0.1101	-0.1810	-0.2599**
	(0.4133)	(0.1698)	(0.0962)
Num.Obs.	43195	42980	43110
R2	0.130	0.130	0.130
R2 Adj.	0.115	0.115	0.115
AIC	46836.6	46617.4	46748.5
BIC	50349.3	50128.2	50260.4
RMSE	0.42	0.42	0.42
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table C.6 : Logit Regression Results Primary Education (Gender Differentiated)

	(M:10 km) **Primary Education**	(M: 25 km) **Primary Education**	(M:50 km) **Primary Education**	(F: 10 km) **Primary Education**	(F: 25 km) **Primary Education**	(F: 50 km) **Primary Education**
Active	-0.1505	-0.0029	-0.2245*	-0.6583	-0.3494+	-0.0824
	(0.4983)	(0.2009)	(0.0959)	(0.4077)	(0.1842)	(0.0820)
Inactive	-10.6646***	-1.7490+	-0.4319	-0.2900	-0.1705	-0.0290
	(0.3042)	(1.0379)	(0.2750)	(0.6908)	(0.5249)	(0.2100)
Religion	0.1091+	0.1044+	0.1094+	0.0037	0.0093	0.0032
	(0.0600)	(0.0601)	(0.0602)	(0.0584)	(0.0587)	(0.0584)
Urban	-0.0535	-0.0513	-0.0516	-0.0452	-0.0408	-0.0459
	(0.0405)	(0.0407)	(0.0406)	(0.0301)	(0.0306)	(0.0302)
Drought	2.4821*	2.6264*	2.5002*	-0.2460	-0.3039	-0.1814
	(1.0443)	(1.0445)	(1.0447)	(1.0222)	(1.0275)	(1.0229)
Rain	-0.0020***	-0.0020***	-0.0020***	-0.0028***	-0.0028***	-0.0028***
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Agri. Land	0.0004	0.0002	0.0005	0.0027	0.0029	0.0028
	(0.0029)	(0.0029)	(0.0029)	(0.0026)	(0.0026)	(0.0026)
Exp. Time	-0.0296	-0.0307	-0.0037	0.0544	0.0579*	0.0072
	(0.0696)	(0.0311)	(0.0175)	(0.0526)	(0.0250)	(0.0147)
Age (18 - 25)	-0.6886***	-0.6836***	-0.6497***	-0.4157***	-0.4202***	-0.4095***
	(0.0715)	(0.0721)	(0.0725)	(0.0678)	(0.0683)	(0.0688)
Age (26 – 35)	-0.3538***	-0.3532***	-0.3422***	-0.2866***	-0.2928***	-0.2856***
	(0.0611)	(0.0613)	(0.0612)	(0.0597)	(0.0598)	(0.0598)
Age (36 -45)	-0.2413***	-0.2409***	-0.2405***	-0.1916**	-0.1880**	-0.1914**
	(0.0600)	(0.0601)	(0.0600)	(0.0607)	(0.0607)	(0.0607)
Age (56 -65)	0.0880	0.0864	0.0858	0.1030	0.1044	0.1032
	(0.0722)	(0.0722)	(0.0721)	(0.0798)	(0.0798)	(0.0798)
Age (66 +)	0.0063	0.0034	0.0033	0.0280	0.0308	0.0265
	(0.0862)	(0.0863)	(0.0862)	(0.1035)	(0.1035)	(0.1035)
Num.Obs.	21300	21204	21262	21688	21569	21641
R2	0.144	0.145	0.144	0.129	0.129	0.128
R2 Adj.	0.113	0.113	0.113	0.100	0.100	0.099
AIC	22529.1	22440.4	22498.6	24557.7	24422.1	24509.2
BIC	25691.8	25601.3	25660.6	27711.6	27573.8	27662.2
RMSE	0.41	0.41	0.41	0.43	0.43	0.43
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. M = Male. F = Female.

Table C.7 : Logit Regression Results Secondary Education

	(10 km) **Secondary Education**	(25 km) **Secondary Education**	(50 km) **Secondary Education**
Active	0.0288	-0.0021	0.2362***
	(0.2764)	(0.1191)	(0.0558)
Inactive	0.1569	0.6158+	0.0485
	(0.4782)	(0.3379)	(0.1403)
Gender	0.4024***	0.4007***	0.4015***
	(0.0220)	(0.0221)	(0.0220)
Religion	-0.3916***	-0.3951***	-0.3950***
	(0.0401)	(0.0402)	(0.0402)
Urban	-0.0112	-0.0128	-0.0113
	(0.0169)	(0.0171)	(0.0170)
Drought	-2.6833***	-2.7446***	-2.7374***
	(0.6848)	(0.6867)	(0.6866)
Rain	0.0017***	0.0017***	0.0016***
	(0.0003)	(0.0003)	(0.0003)
Agri. Land	0.0050**	0.0051**	0.0049**
	(0.0017)	(0.0017)	(0.0017)
Exp. Time	0.0129	0.0028	0.0053
	(0.0385)	(0.0170)	(0.0097)
Age (18 -25)	0.9906***	0.9840***	0.9478***
	(0.0444)	(0.0447)	(0.0451)
Age (26 - 35)	0.5606***	0.5592***	0.5468***
	(0.0405)	(0.0406)	(0.0406)
Age (36 - 45)	0.4420***	0.4412***	0.4389***
	(0.0417)	(0.0417)	(0.0417)
Age (56 - 65)	-0.3567***	-0.3565***	-0.3545***
	(0.0539)	(0.0540)	(0.0539)
Age (66+)	-0.9064***	-0.9058***	-0.9033***
	(0.0715)	(0.0715)	(0.0716)
Num.Obs.	43218	43003	43133
R2	0.162	0.162	0.162
R2 Adj.	0.148	0.148	0.149
AIC	50497.3	50220.7	50351.7
BIC	54018.9	53740.3	53872.5
RMSE	0.44	0.44	0.44
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- +p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table C. 8: Logit Regression Results Secondary Education (Interaction)

	(10 km) **Secondary Education**	(25 km) **Secondary Education**	(50 km) **Secondary Education**
Active	0.2067	-0.0328	0.1573*
	(0.3108)	(0.1357)	(0.0672)
Inactive	0.1513	0.6156+	0.0482
	(0.4772)	(0.3379)	(0.1403)
Gender	0.4041***	0.3993***	0.3894***
	(0.0220)	(0.0223)	(0.0228)
Religion	-0.3915***	-0.3952***	-0.3950***
	(0.0401)	(0.0402)	(0.0402)
Urban	-0.0111	-0.0128	-0.0115
	(0.0169)	(0.0171)	(0.0170)
Drought	-2.6846***	-2.7455***	-2.7477***
	(0.6848)	(0.6867)	(0.6867)
Rain	0.0017***	0.0017***	0.0016***
	(0.0003)	(0.0003)	(0.0003)
Agri. Land	0.0050**	0.0051**	0.0049**
	(0.0017)	(0.0017)	(0.0017)
Exp. Time	0.0141	0.0029	0.0054
	(0.0380)	(0.0169)	(0.0098)
Age (18 – 25)	0.9905***	0.9840***	0.9478***
	(0.0444)	(0.0447)	(0.0451)
Age (26 - 35)	0.5607***	0.5591***	0.5465***
	(0.0405)	(0.0406)	(0.0406)
Age (36 - 45)	0.4420***	0.4412***	0.4390***
	(0.0417)	(0.0417)	(0.0417)
Age (56 - 65)	-0.3569***	-0.3564***	-0.3538***
	(0.0539)	(0.0540)	(0.0539)
Age (66+)	-0.9067***	-0.9056***	-0.9017***
	(0.0715)	(0.0715)	(0.0716)
Active × Gender	-0.4148	0.0662	0.1756*
	(0.3517)	(0.1544)	(0.0878)
Num.Obs.	43218	43003	43133
R2	0.162	0.162	0.162
R2 Adj.	0.148	0.148	0.149
AIC	50497.8	50222.5	50349.5
BIC	54028.1	53750.8	53879.1
RMSE	0.44	0.44	0.44
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- +p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table C. 9: Logit Regression Results Secondary Education (Gender Differentiated)

	(M: 10 km) **Secondary Education**	(M:25 km) **Secondary Education**	(M:50 km) **Secondary Education**	(F: 10 km) **Secondary Education**	(F: 25 km) **Secondary Education**	(F: 50 km) **Secondary Education**
Active	-0.5269	-0.3080+	0.2929***	0.3561	0.2614	0.2057**
	(0.4259)	(0.1747)	(0.0842)	(0.3648)	(0.1655)	(0.0776)
Inactive	0.1390	0.7979	0.1027	0.2627	0.6260	0.0252
	(0.7415)	(0.5804)	(0.1994)	(0.6977)	(0.4706)	(0.2078)
Religion	-0.3682***	-0.3710***	-0.3727***	-0.4425***	-0.4498***	-0.4476***
	(0.0548)	(0.0550)	(0.0548)	(0.0613)	(0.0616)	(0.0615)
Urban	-0.0112	-0.0090	-0.0124	-0.0145	-0.0202	-0.0138
	(0.0244)	(0.0246)	(0.0246)	(0.0245)	(0.0250)	(0.0247)
Drought	-2.7041**	-2.8446**	-2.7652**	-2.8071**	-2.7546**	-2.8575**
	(0.9391)	(0.9430)	(0.9418)	(1.0545)	(1.0572)	(1.0573)
Rain	0.0013**	0.0013**	0.0013**	0.0016***	0.0017***	0.0016***
	(0.0004)	(0.0004)	(0.0004)	(0.0005)	(0.0005)	(0.0005)
Agri. Land	0.0066**	0.0069**	0.0064**	0.0037	0.0035	0.0035
	(0.0024)	(0.0024)	(0.0024)	(0.0025)	(0.0025)	(0.0025)
Exp. Time	0.0676	0.0737**	0.0116	-0.0120	-0.0622**	-0.0051
	(0.0623)	(0.0263)	(0.0144)	(0.0514)	(0.0241)	(0.0139)
Age (18 - 26)	0.9863***	0.9750***	0.9281***	1.0682***	1.0678***	1.0390***
	(0.0618)	(0.0623)	(0.0629)	(0.0671)	(0.0676)	(0.0683)
Age (26 - 35)	0.4651***	0.4594***	0.4464***	0.6987***	0.7024***	0.6899***
	(0.0557)	(0.0559)	(0.0559)	(0.0614)	(0.0616)	(0.0616)
Age (36 -45)	0.4086***	0.4068***	0.4064***	0.4984***	0.4993***	0.4956***
	(0.0570)	(0.0571)	(0.0570)	(0.0629)	(0.0630)	(0.0630)
Age (56-65)	-0.2559***	-0.2544***	-0.2523***	-0.5551***	-0.5576***	-0.5551***
	(0.0701)	(0.0702)	(0.0701)	(0.0882)	(0.0882)	(0.0882)
Age (66 +)	-0.7736***	-0.7711***	-0.7680***	-1.2729***	-1.2761***	-1.2721***
	(0.0888)	(0.0890)	(0.0889)	(0.1323)	(0.1323)	(0.1325)
Num.Obs.	21369	21273	21331	21754	21635	21707
R2	0.155	0.156	0.156	0.184	0.184	0.184
R2 Adj.	0.128	0.129	0.129	0.157	0.157	0.157
AIC	25776.0	25637.2	25707.1	24804.2	24651.9	24728.7
BIC	28979.8	28839.2	28910.2	27991.3	27836.7	27914.9
RMSE	0.45	0.45	0.45	0.43	0.43	0.43
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. M = Male. F = Female.

Table C. 10: Regression Results Ethnicity

	(10 km) **Education**	(25 km) **Education**	(50 km) **Education**
Active	0.4347*	0.1948*	0.0665
	(0.2114)	(0.0867)	(0.0432)
Inactive	0.5769+	0.5961**	0.4420***
	(0.3255)	(0.2189)	(0.1199)
Gender	0.5377***	0.5375***	0.5374***
	(0.0173)	(0.0173)	(0.0173)
Ethnicity	1.0556***	1.0554***	1.0551***
	(0.1125)	(0.1125)	(0.1126)
Urban	0.0591***	0.0585***	0.0590***
	(0.0157)	(0.0160)	(0.0158)
Drought	-1.3605*	-1.3527*	-1.2994*
	(0.5347)	(0.5361)	(0.5352)
Rain	0.0003	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)
Agri. Land	-0.0002	-0.0003	-0.0004
	(0.0015)	(0.0015)	(0.0015)
Exp. Time	-0.0171	-0.0278*	-0.0086
	(0.0292)	(0.0126)	(0.0075)
Age (18 - 25)	0.8154***	0.8114***	0.8046***
	(0.0359)	(0.0362)	(0.0364)
Age (26 - 35)	0.6951***	0.6938***	0.6909***
	(0.0331)	(0.0331)	(0.0331)
Age (36 - 45)	0.3580***	0.3570***	0.3563***
	(0.0333)	(0.0333)	(0.0333)
Age (56 - 65)	-0.4007***	-0.4016***	-0.4008***
	(0.0419)	(0.0419)	(0.0419)
Age (66 +)	-0.8980***	-0.8986***	-0.8989***
	(0.0503)	(0.0504)	(0.0503)
Num.Obs.	43317	43102	43232
R2	0.312	0.312	0.312
R2 Adj.	0.305	0.306	0.306
AIC	173858.7	173041.7	173542.8
BIC	177416.0	176596.9	177099.2
RMSE	1.78	1.78	1.78
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Ethnicity = 1, if the respondent is of American, Chinese or European descent and 0, if not. Ethnicity = 0 is the reference category.

F – Test (25 km): F = 3.39, p < 0.1

F – Test (50 km): F = 9.41, p < 0.01

Table C.11: Regression Results Ethnicity (Interaction)

	(10 km) **Education**	(25 km) **Education**	(50 km) **Education**
Active	0.5439*	0.2352*	0.0515
	(0.2334)	(0.1001)	(0.0528)
Inactive	0.5706+	0.5963**	0.4420***
	(0.3262)	(0.2189)	(0.1199)
Gender	0.5387***	0.5391***	0.5353***
	(0.0173)	(0.0175)	(0.0180)
Ethnicity	1.0556***	1.0551***	1.0551***
	(0.1125)	(0.1125)	(0.1125)
Urban	0.0591***	0.0585***	0.0589***
	(0.0157)	(0.0160)	(0.0158)
Drought	-1.3610*	-1.3510*	-1.3021*
	(0.5348)	(0.5361)	(0.5353)
Rain	0.0003	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)
Agri. Land	-0.0002	-0.0003	-0.0004
	(0.0015)	(0.0015)	(0.0015)
Exp. Time	-0.0155	-0.0279*	-0.0086
	(0.0296)	(0.0126)	(0.0075)
Age (18 - 25)	0.8153***	0.8115***	0.8046***
	(0.0359)	(0.0362)	(0.0364)
Age (26 - 36)	0.6952***	0.6938***	0.6909***
	(0.0331)	(0.0331)	(0.0331)
Age (36 - 45)	0.3580***	0.3570***	0.3563***
	(0.0333)	(0.0333)	(0.0333)
Age_56_65	-0.4007***	-0.4017***	-0.4007***
	(0.0419)	(0.0419)	(0.0419)
Age (66 +)	-0.8982***	-0.8989***	-0.8986***
	(0.0503)	(0.0504)	(0.0503)
Active × Gender	-0.2567	-0.0845	0.0324
	(0.2606)	(0.1102)	(0.0628)
Num.Obs.	43317	43102	43232
R2	0.312	0.312	0.312
R2 Adj.	0.305	0.306	0.306
AIC	173859.9	173043.2	173544.5
BIC	177425.8	176607.2	177109.7
RMSE	1.78	1.78	1.78
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Ethnicity = 1, if the respondent is of American, Chinese or European descent and 0, if not. Ethnicity = 0 is the reference category.

Table C. 12: Regression Results Ethnicity (Gender Differentiated)

	(M:10 km) **Education**	(M:25 km) **Education**	(M: 50 km) **Education**	(F:10 km) **Education**	(F: 25 km) **Education**	(F: 50 km) **Education**
Active	0.4410	0.2222+	0.1171+	0.3966	0.1431	0.0156
	(0.3333)	(0.1227)	(0.0613)	(0.2732)	(0.1238)	(0.0606)
Inactive	0.6633	0.5611*	0.2203	0.6353	0.7150*	0.6195***
	(0.4362)	(0.2658)	(0.1603)	(0.4826)	(0.3574)	(0.1750)
Ethnicity	1.0035***	1.0034***	1.0011***	1.0860***	1.0856***	1.0855***
	(0.1608)	(0.1608)	(0.1609)	(0.1542)	(0.1542)	(0.1541)
Urban	0.0493*	0.0477*	0.0478*	0.0691**	0.0690**	0.0700**
	(0.0229)	(0.0232)	(0.0230)	(0.0214)	(0.0220)	(0.0214)
Drought	-1.4810+	-1.4927*	-1.4536+	-0.9581	-0.9276	-0.8552
	(0.7583)	(0.7602)	(0.7598)	(0.7551)	(0.7572)	(0.7553)
Rain	0.0000	0.0000	0.0000	0.0004	0.0004	0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Agri. Land	-0.0007	-0.0007	-0.0008	0.0006	0.0004	0.0003
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Exp-Time	-0.0337	-0.0264+	-0.0101	0.0031	-0.0285	-0.0070
	(0.0409)	(0.0157)	(0.0102)	(0.0418)	(0.0197)	(0.0110)
Age (18 – 25)	0.6982***	0.6954***	0.6862***	0.9638***	0.9608***	0.9572***
	(0.0523)	(0.0527)	(0.0530)	(0.0497)	(0.0500)	(0.0504)
Age (26 - 35)	0.6078***	0.6054***	0.6032***	0.7962***	0.7972***	0.7931***
	(0.0481)	(0.0482)	(0.0482)	(0.0455)	(0.0456)	(0.0456)
Age (36 - 45)	0.3244***	0.3228***	0.3232***	0.4073***	0.4072***	0.4056***
	(0.0479)	(0.0479)	(0.0479)	(0.0464)	(0.0464)	(0.0464)
Age (56 - 65)	-0.3296***	-0.3303***	-0.3292***	-0.5356***	-0.5366***	-0.5366***
	(0.0578)	(0.0578)	(0.0578)	(0.0605)	(0.0605)	(0.0605)
Age (66+)	-0.8611***	-0.8608***	-0.8599***	-1.0527***	-1.0544***	-1.0557***
	(0.0673)	(0.0674)	(0.0674)	(0.0764)	(0.0765)	(0.0764)
Num.Obs.	21448	21352	21410	21869	21750	21822
R2	0.287	0.287	0.287	0.350	0.351	0.351
R2 Adj.	0.273	0.274	0.273	0.338	0.339	0.339
AIC	86851.8	86493.8	86721.3	86813.3	86354.6	86622.1
BIC	90112.9	89753.1	89981.7	90082.4	89621.4	89890.3
RMSE	1.80	1.80	1.80	1.73	1.73	1.73
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes	Yes	Yes	Yes

- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. M = Male. F = Female.

Table C.13: Regression Results Urban

	Education	Education	Education
Active	0.4062+	0.2383**	0.0882*
	(0.2082)	(0.0863)	(0.0427)
Inactive	0.4412	0.5197*	0.4133***
	(0.3285)	(0.2182)	(0.1172)
Gender	0.5421***	0.5421***	0.5418***
	(0.0169)	(0.0170)	(0.0169)
Religion	-0.4696***	-0.4754***	-0.4726***
	(0.0309)	(0.0309)	(0.0309)
Urban	0.8915***	0.8934***	0.8928***
	(0.0223)	(0.0224)	(0.0224)
Drought	-0.9329+	-0.9154+	-0.8772+
	(0.5241)	(0.5254)	(0.5245)
Rain	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)
Agri. Land	-0.0005	-0.0005	-0.0007
	(0.0014)	(0.0014)	(0.0014)
Exp. Time	-0.0200	-0.0319*	-0.0082
	(0.0292)	(0.0124)	(0.0074)
Age (18 - 25)	0.8191***	0.8130***	0.8052***
	(0.0340)	(0.0343)	(0.0345)
Age (26 - 35)	0.6830***	0.6817***	0.6777***
	(0.0316)	(0.0316)	(0.0316)
Age (36 - 45)	0.3468***	0.3462***	0.3449***
	(0.0326)	(0.0326)	(0.0326)
Age (56 - 65)	-0.3865***	-0.3871***	-0.3864***
	(0.0413)	(0.0413)	(0.0413)
Age (66 +)	-0.8822***	-0.8826***	-0.8826***
	(0.0496)	(0.0496)	(0.0496)
Num.Obs.	43317	43102	43232
R2	0.341	0.341	0.341
R2 Adj.	0.334	0.335	0.335
AIC	172010.9	171196.2	171692.8
BIC	175568.2	174751.5	175249.2
RMSE	1.75	1.75	1.75
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Urban = 1 if the respondent lives in an urban enumeration area. Urban = 0, if the respondent lives in a rural enumeration area. Urban = 0 is the reference category. M = Male. F = Female.

F – Test (50 km): F = 7.37, p < 0.01

Table C. 14: Regression Results Urban (Interaction)

	Education	**Education**	**Education**
Active	0.5306*	0.2810**	0.0723
	(0.2248)	(0.0990)	(0.0522)
Inactive	0.4341	0.5199*	0.4133***
	(0.3293)	(0.2182)	(0.1172)
Gender	0.5432***	0.5438***	0.5395***
	(0.0169)	(0.0172)	(0.0176)
Religion	-0.4696***	-0.4753***	-0.4726***
	(0.0309)	(0.0309)	(0.0309)
Urban	0.8916***	0.8934***	0.8928***
	(0.0223)	(0.0224)	(0.0224)
Drought	-0.9335+	-0.9136+	-0.8800+
	(0.5241)	(0.5254)	(0.5246)
Rain	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)
Agri. Land	-0.0005	-0.0005	-0.0007
	(0.0014)	(0.0014)	(0.0014)
Exp. Time	-0.0182	-0.0320**	-0.0082
	(0.0297)	(0.0124)	(0.0074)
Age (18 - 25)	0.8190***	0.8131***	0.8052***
	(0.0340)	(0.0343)	(0.0345)
Age (26 - 35)	0.6831***	0.6817***	0.6776***
	(0.0316)	(0.0316)	(0.0316)
Age (36 - 45)	0.3468***	0.3462***	0.3449***
	(0.0326)	(0.0326)	(0.0326)
Age (56 - 65)	-0.3866***	-0.3872***	-0.3862***
	(0.0413)	(0.0413)	(0.0413)
Age (66+)	-0.8825***	-0.8828***	-0.8823***
	(0.0496)	(0.0496)	(0.0496)
Active × Gender	-0.2926	-0.0893	0.0342
	(0.2662)	(0.1096)	(0.0622)
Num.Obs.	43317	43102	43232
R2	0.341	0.341	0.341
R2 Adj.	0.334	0.335	0.335
AIC	172011.8	171197.7	171694.5
BIC	175577.7	174761.6	175259.7
RMSE	1.75	1.75	1.75
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Urban = 1 if the respondent lives in an urban enumeration area. Urban = 0, if the respondent lives in a rural enumeration area. Urban = 0 is the reference category. M = Male. F = female.

Table C.15: Regression Results Urban (Gender Differentiated)

	(M:10 km) Education	(M: 25 km) Education	(M: 50 km) Education	(F: 10 km) Education	(F: 25 km) Education	(F: 50 km) Education
Active	0.4435	0.2676*	0.1451*	0.3492	0.1850	0.0317
	(0.3478)	(0.1239)	(0.0607)	(0.2576)	(0.1218)	(0.0599)
Inactive	0.5318	0.4803+	0.2052	0.4951	0.6420+	0.5788***
	(0.4211)	(0.2609)	(0.1575)	(0.4999)	(0.3562)	(0.1705)
Religion	-0.4886***	-0.4917***	-0.4918***	-0.4805***	-0.4887***	-0.4826***
	(0.0441)	(0.0442)	(0.0441)	(0.0431)	(0.0431)	(0.0431)
Urban	0.9355***	0.9379***	0.9362***	0.8564***	0.8571***	0.8580***
	(0.0321)	(0.0322)	(0.0321)	(0.0307)	(0.0309)	(0.0308)
Drought	-1.0172	-1.0111	-0.9921	-0.5428	-0.5099	-0.4497
	(0.7423)	(0.7441)	(0.7439)	(0.7429)	(0.7448)	(0.7429)
Rain	0.0000	0.0000	0.0000	0.0002	0.0002	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)
Agri. Land	-0.0012	-0.0012	-0.0014	0.0006	0.0004	0.0003
	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Exp. Time	-0.0467	-0.0310*	-0.0102	0.0080	-0.0321+	-0.0060
	(0.0434)	(0.0158)	(0.0101)	(0.0411)	(0.0191)	(0.0108)
Age (18 -25)	0.6744***	0.6694***	0.6580***	0.9933***	0.9882***	0.9848***
	(0.0491)	(0.0495)	(0.0499)	(0.0473)	(0.0476)	(0.0481)
Age (26 -35)	0.5683***	0.5659***	0.5619***	0.8087***	0.8097***	0.8051***
	(0.0457)	(0.0458)	(0.0458)	(0.0436)	(0.0437)	(0.0437)
Age (36 -45)	0.2998***	0.2987***	0.2982***	0.4087***	0.4088***	0.4070***
	(0.0467)	(0.0468)	(0.0467)	(0.0455)	(0.0455)	(0.0455)
Age (56 -65)	-0.3184***	-0.3186***	-0.3174***	-0.5208***	-0.5214***	-0.5216***
	(0.0566)	(0.0566)	(0.0566)	(0.0599)	(0.0600)	(0.0600)
Age (66+)	-0.8579***	-0.8571***	-0.8561***	-1.0249***	-1.0268***	-1.0274***
	(0.0662)	(0.0663)	(0.0663)	(0.0749)	(0.0751)	(0.0750)
Num.Obs.	21448	21352	21410	21869	21750	21822
R2	0.320	0.320	0.320	0.377	0.378	0.378
R2 Adj.	0.306	0.307	0.306	0.365	0.366	0.366
AIC	85850.8	85494.2	85719.9	85896.3	85439.3	85703.5
BIC	89111.9	88753.5	88980.3	89165.4	88706.1	88971.7
RMSE	1.76	1.76	1.76	1.69	1.69	1.69
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes	Yes	Yes	Yes

- + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Urban = 1 if the respondent lives in an urban enumeration area. Urban = 0, if the respondent lives in a rural enumeration area. Urban = 0 is the reference category. M = Male. F = female.

Appendix D: Testing the Causal Mechanisms

To test the causal mechanisms, I operationalized *active* and *inactive* according to Wegenast et al. (2022), without considering the age of respondents and the timing of the LSLAs, as considering these is not necessary when the dependent variable is not education. Therefore, *active* is coded as 1 for those within the buffer of an active LSLA, and *inactive* for those within the buffer of an inactive LSLA. The reference group consists of individuals not located in any LSLA buffer. I removed respondents who are in the buffer of both an active and an inactive LSLA. For the operationalization of control variables, I exclusively used variables from the Afrobarometer dataset. Table D.1 details the operationalization of all variables used in my analysis. the regression models, the reference category for binary variables is always the group that is assigned a value of 0.

Table D.1: Operationalization of Variables

Variable	**Operationalization**
Active	1 = The respondent is within the buffer of an active LSLA. 0 = The respondent is not within the buffer of an active LSLA.
Inactive	1 = The respondent is within the buffer of an inactive LSLA. 0 = The respondent is not within the buffer of an inactive LSLA.
School	1 = There is a school in the primary enumeration area of the respondent. 0 = There is no school in the enumeration area of the respondent.
Urban	1 = The respondent lives in an urban enumeration area. 0 = The respondent lives in a rural enumeration area.

Insecurity	1 = The respondent and his or her family felt insecure several times, many times, or always while walking in their neighborhood in the past year. 0 = The respondent and his or her family felt insecure never, or just once or twice while walking in their neighborhood in the past year.
Electricity	1 = There is an electricity grid in the enumeration area of the respondent. 0 = There is no electricity grid in the enumeration area of the respondent.
Market Stall	1 = There is a market stall in the enumeration area of the respondent. 0 = There is no market stall in the enumeration area of the respondent.
Gender	1 = Male 0 = Female
Remittances	How often does the household in which the respondent lives receive remittances from abroad? 0 = never, 1 = Less than once a year, 2 = At least once a year, 3 = At least every six months, 4 = At least every three months, 5 = At least once a month
Food insecurity	1 = The respondent or anyone in the family of the respondent did not have enough to eat several times, many times, or always in the past year. 0 = The respondent or anyone in the family of the respondent did not have enough to eat never, or just once or twice in the past year.
No income	1 = The respondent or anyone in his family went without cash income many times, several times, or always in the past year. 0 = The respondent or anyone in his family went without cash income never, or just once or twice in the past year.

Community	1 = The respondent is an active member or a leader of a community organization. 0 = The respondent is not a member or is an inactive member of a community organization
Age	Age of the Respondent at the time of the survey.
Education	Operationalized like in the main text (Chapter 4.2).
Household	Number of household members.

To enhance confidence in my theoretical mechanisms, I tested if LSLAs negatively impact school infrastructure, thus affecting the supply side of education. I conducted a logistic regression and controlled for whether the respondent lives in an urban or rural area, as infrastructure tends to be better in urban areas of developing countries (Hlalele, 2014). Moreover, I also controlled for neighborhood security, which can affect both infrastructure and the placement of LSLAs (Balestri & Maggioni, 2019). Additionally, I used access to electricity as a proxy for state capacity, which can influence infrastructure (Koren & Sarbahi, 2018).

The results of the logistic regressions are shown in Table D.2, indicating that LSLAs tend to improve school infrastructure. Looking at the school infrastructure within a 10-kilometer buffer of the LSLAs, there is a statistically significant positive effect on school infrastructure ($F = 30.882$, $p < 0.001$). This can potentially be attributed to corporate social responsibility programs by international investors. This finding boosts confidence in my theory, as it indicates that the negative impact of LSLAs on education does not stem from a deterioration of the education supply side. However, the results should be interpreted with caution, as they do not reflect the influence of LSLAs on school infrastructure during the period when the respondents were between 0 and 16 years old.

Table D.2 : Logit Regression Results School Infrastructure

	(10 km) School	(25 km) School	(50 km) School
Active	0.32*	-0.11	-0.07
	(0.14)	(0.07)	(0.06)
Inactive	-0.86***	-1.63***	-1.03***
	(0.16)	(0.13)	(0.11)
Urban	0.16***	0.16**	0.16**
	(0.05)	(0.05)	(0.05)
Insecurity	0.01	0.01	0.01
	(0.04)	(0.04)	(0.04)
Electricity	1.42***	1.44***	1.45***
	(0.05)	(0.05)	(0.05)
Num.Obs.	30877	30805	29831
R2	0.171	0.175	0.173
R2 Adj.	0.159	0.162	0.160
AIC	25363.1	25224.6	24701.2
BIC	26972.3	26833.4	26287.1
RMSE	0.36	0.36	0.36
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Next, I examined whether LSLAs have a statistically significant negative impact on food insecurity and income. The results are presented in tables D.3 and D.4. In both regressions, I controlled for several factors including whether the respondent lives in an urban area, where food insecurity is lower and income is higher (De Magalhães, 2018; Bjornlund et al., 2022), whether the respondent receives remittances which can generate additional income and thereby reduce food insecurity, whether the respondent is a member of a community association which can provide financial support and mitigate food insecurity (Fisher & Lewin, 2013), whether the respondent has a market stall nearby, used as a proxy for economic activity, the number of people in the household, as larger households may leave fewer resources per person (Biyase & Zwane, 2018), and whether the respondent lives in an insecure area, which can diminish income prospects and exacerbate food insecurity (Justino, 2012; Kemmerling et al., 2022). Additionally, I considered gender differences, since men in developing countries often have higher incomes than women and are less frequently affected by food insecurity (Broussard, 2020; Kim, 2020). Additionally, I accounted for age, as older respondents may no longer be able to work, which potentially affects their ability to reduce food insecurity.

Table D.3 : Logit Regression Results No Income

	(10 km)	(25 km)	(50 km)
	No Income	**No Income**	**No Income**
Active	-0.027	-0.021	0.047
	(0.088)	(0.047)	(0.044)
Inactive	0.274	-0.193	-0.223*
	(0.194)	(0.123)	(0.105)
Age	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)
Urban	-0.492***	-0.492***	-0.492***
	(0.029)	(0.029)	(0.029)
Gender	-0.076***	-0.075***	-0.076***
	(0.023)	(0.023)	(0.023)
Market	-0.096**	-0.093**	-0.091**
	(0.031)	(0.031)	(0.031)
Remittances	-0.132***	-0.131***	-0.129***
	(0.008)	(0.008)	(0.008)
Community	-0.081**	-0.082**	-0.078**
	(0.028)	(0.028)	(0.029)
Household	0.016**	0.016**	0.015**
	(0.005)	(0.005)	(0.006)
Insecurity	0.581***	0.582***	0.583***
	(0.029)	(0.029)	(0.029)
Num.Obs.	45035	44966	43962
R2	0.194	0.194	0.196
R2 Adj.	0.180	0.180	0.182
AIC	48147.6	48071.3	46894.9
BIC	51677.2	51600.3	50406.1
RMSE	0.42	0.42	0.42
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results indicate that LSLAs have neither a statistically significant negative impact on food insecurity nor on income, which weakens confidence in my theoretical mechanisms.

Table D. 4: Logit Regression Results Food Insecurity

	(10 km)	(25 km)	(50 km)
	Food Insecurity	**Food Insecurity**	**Food Insecurity**
Active	-0.095	-0.049	-0.046
	(0.090)	(0.047)	(0.042)
Inactive	-0.346	-0.018	-0.109
	(0.200)	(0.119)	(0.097)
Age	0.011***	0.011***	0.011***
	(0.001)	(0.001)	(0.001)
Urban	-0.410***	-0.411***	-0.411***
	(0.030)	(0.030)	(0.030)
Gender	-0.117***	-0.116***	-0.115***
	(0.022)	(0.022)	(0.023)
Market	-0.093**	-0.094**	-0.096**
	(0.030)	(0.030)	(0.030)
Remittances	-0.123***	-0.123***	-0.120***
	(0.009)	(0.009)	(0.009)
Community	-0.098***	-0.099***	-0.099***
	(0.027)	(0.027)	(0.028)
Household	0.008	0.008	0.006
	(0.005)	(0.005)	(0.005)
Insecurity	0.640***	0.639***	0.636***
	(0.026)	(0.026)	(0.027)
Num.Obs.	44880	44811	43807
R2	0.137	0.136	0.138
R2 Adj.	0.122	0.122	0.123
AIC	49183.5	49120.2	48026.8
BIC	52676.9	52613.0	51501.8
RMSE	0.43	0.43	0.43
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, I examined the influence of food insecurity and income on education. The results, displayed in Table D.5, indicate that both lack of income and food insecurity, as expected, have a statistically significant negative impact on education. I used the same control variables because, as outlined in my theoretical framework, food insecurity, income, and education are closely interconnected. I reported the results for the different datasets corresponding to each buffer size used, but in this case, buffer size is not relevant because I am not using the active and inactive variables.

Table D.5: Regression Results Causal Mechanisms

	(10 km)	(25 km)	(50 km)
	Education	**Education**	**Education**
Food Insecurity	-0.420***	-0.422***	-0.418***
	(0.019)	(0.019)	(0.020)
No Income	-0.389***	-0.389***	-0.385***
	(0.021)	(0.021)	(0.021)
Age	-0.034***	-0.034***	-0.034***
	(0.001)	(0.001)	(0.001)
Urban	0.571***	0.569***	0.565***
	(0.024)	(0.024)	(0.024)
Gender	0.520***	0.520***	0.512***
	(0.017)	(0.017)	(0.017)
Market	0.113***	0.112***	0.111***
	(0.022)	(0.023)	(0.023)
Electricity	0.613***	0.615***	0.619***
	(0.026)	(0.026)	(0.026)
Community	0.408***	0.408***	0.408***
	(0.021)	(0.021)	(0.021)
Household	0.008*	0.008*	0.008*
	(0.004)	(0.004)	(0.004)
Insecurity	0.052*	0.051*	0.061**
	(0.020)	(0.020)	(0.020)
Num.Obs.	45770	45699	44679
R2	0.365	0.365	0.367
R2 Adj.	0.359	0.359	0.361
AIC	181919.9	181638.0	177471.1
BIC	185578.4	185295.8	181110.7
RMSE	1.75	1.75	1.75
Std.Errors	Heteroskedasticity-robust	Heteroskedasticity-robust	Heteroskedasticity-robust
FE: region	Yes	Yes	Yes

- + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Overall, it can be said that the results of my causal mechanism testing are mixed and not sufficient to increase confidence in my theory. The causal mechanisms tested here also form the basis for my theory regarding the gendered impacts of LSLAs on education. However, I am unable to test changes in the gender-specific educational preferences of households. This implies that households are a black box, preventing me from investigating how LSLAs influence household decisions on education.

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ISSN: **2701-3456**
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