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Locust Infestations and Individual School Dropout: Evidence from Africa *

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Abstract

This paper examines the effect of desert locust infestations on school enrollment of children and young adults between 3 and 24 years of age. We combine individual and household survey data from the 2005-2019 Demographic and Health Surveys (DHS) Program with data on the spatial distribution of locust events in Africa. We show that months of exposure to locust infestations have a negative and statistically significant impact on individual schooling status. We find that individuals from farming households are affected more negatively by locust infestations than individuals from non-farming households. We also find that individuals from poorer farming households have a higher school dropout rate than individuals from wealthier farming households, highlighting the role of negative income shocks as a possible transmission mechanism for the effects of desert locust events. Our results also show that the estimated effect is amplified by the household's head educational status. A series of additional robustness tests further corroborate our main findings. We provide a quantitative assessment of the impact of a permanent 1.5 $^{\circ}C$ rise in global temperature on the frequency of locust events and possible implications for schooling outcomes over time. The results show that a 1.5 $^{\circ}C$ rise in temperature will decrease accumulated years of schooling by about 1.2 years over a period of 10 years.

Keywords: Desert Locust; Demographic and Health Surveys (DHS) Program; School Enrollment; Income Shocks; Current Schooling; Farmers; Africa

JEL Classification Numbers: I21, O12, Q54

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1 Introduction

According to the Food and Agriculture Organization (FAO), desert locusts are one of the most devastating migratory insect pests worldwide, with impacts on human populations ranging from starvation to income shocks and internal migration. A sudden infestation can cause severe crop damage and yield loss, with a 1 km^2 swarm consuming the same amount of food in a single day as 35,000 people (FAO, 2022). Outbreaks of desert locusts pose a particular threat to the livelihoods of people in rural Africa, where agriculture is critical to food security and rural employment. Locust infestations can prevent the successful cultivation of many crops, resulting in extreme income volatility in farming households. The effect of locust infestations is compounded by the lack of insurance against natural disasters and the underdeveloped state of credit markets in these regions, making mitigation strategies even more challenging (Karlan et al., 2014). This increases the pressure on people who are already facing severe socioeconomic problems and are especially vulnerable to the effects of climate change and conflict. As mentioned, households exposed to these shocks might likely invest less in their wards' education to smooth consumption or achieve household food security (Newman and Tarp, 2020).

Estimating the causal impacts of exogenous income shocks on individual school status is often difficult. Prior work exploiting exogenous variation in weather conditions to examine the impact of income shocks on, for example, conflict likelihood or schooling has yet to entirely rule out the possibility that the outcome of interest could be directly affected by the source of exogenous variation. Heavy rainfall events, for example, might affect school enrollment status by damaging buildings or road infrastructures in other ways than through changes in household income.

In this paper, we examine the effect of unexpected locust shocks on individual schooling, and estimate differential effects for farming and non-farming households. We interpret the occurrence of locust shocks as a substitute for exogenous fluctuations in agricultural yields and examine whether such events have any detrimental impact on individual schooling decisions. We argue that locust infestations provide a credible source of exogenous income variation for farming households as these events affect individual school enrollment status solely through changes in crop yields and pasture lands, that is, through the income source of farming households.

We combine information on geo-coded locust events with individual and household survey data to quantify the effect of months of locus infestation on school enrollment status across time. We use new spatially disaggregated data on locust occurrences (swarms and bands) in Africa between 1985 and 2020, as compiled by the Desert Locust Information Service (DLIS) of the United Nations Food and Agriculture Organization (FAO). We match the locust infestation data with household survey data from the Demographic and Health Surveys (DHS) Program, which provides information on occupational and academic records, possessions, household structures, and demographics for more than 1.5 million households, mostly from rural survey locations. The rural character of the sample is underscored by remote-sensing data on nighttime light emissions and agricultural land suitability. The data show that more than half of the sample is engaged in farming activities, indicating that most of the area's food sources and income depend heavily on agricultural yields.

In the empirical analysis, we take advantage of the exogenous timing of locust events across locations. We use this information to compare the school enrollment status of individuals living in close proximity to locust events, considering a 50 km radius around survey locations. We construct precise and individual-specific measures of locust exposure by calculating monthly bins of exposure to locust infestations relative to the age of survey respondents at the survey date. Thus, we construct age-specific treatment indicators of whether individuals were subject to locust shocks when they were school-aged, defined as 3 to 24 years of age. Based on this information, we examine the impact of past locust events on individual school enrollment status, comparing individuals in farming and non-farming households.

The baseline estimates suggest that school-aged individuals in farming households experience, ceteris paribus, a higher school dropout rate after episodes of severe locust infestations. We estimate that a single monthly locust event experienced 3 to 4 years prior to the DHS survey interview date increased individual school dropout rates by about 1.31 percentage points in farming households compared to non-farming households. Our regression coefficient estimates are similar in both magnitude and statistical significance for locust treatment episodes more than 4 and up to 10 years prior to the DHS interview date. These estimates indicate a persistent rather than short-run transitory impact of locust infestations on individual school dropout.

The results are robust to a full battery of demographic, socioeconomic, bio-geographic, and climatic controls around DHS locations, and to a standard set of individual- and household-level controls. In the baseline set of controls, we also include a full set of DHS regions interacted with survey year and month fixed effects to flexibly control for year-to-year changes in individual school enrollment status due, for example, to regional differences in the provision of schooling services across time and within regions, and seasonal variation in school enrollment status due to differences in agricultural harvest cycles and academic calendars. We also present estimates of the regression model with DHS survey location fixed effects to alleviate concerns about omitted variables related to the environment of the DHS survey location. In this extended model specification, we exploit variation in school enrollment status within the same DHS location, where identification is based on children who have been affected differently by locust shocks due to differences in school age at the time of the survey interview.

We next examine heterogeneous effects of locust exposure on individual school dropout. We show that older school-aged children have a higher probability of being removed from school in the short run, highlighting the need for cheap child labor immediately after locust outbreaks. In contrast, younger school-aged children are negatively affected by long-term infestations, possibly due to delayed school enrollment to cope with the negative economic consequences of such events. We also observe that females are more negatively affected than males in locust-affected farming households. We also test heterogeneous effects of locust exposure on individual school dropout across educational statuses of household heads (no schooling, primary, secondary, and higher education). We find evidence that the effect of past locust infestations on school dropout is more pronounced in households with a lower educational status, consistent with the hypothesis about the preferences of household heads regarding children's education.

We estimate a series of alternative model specifications to test the robustness of the baseline findings. First, we show that the main results are not sensitive to the definition of different buffer sizes (20, 30, and 40 km) around DHS locations that affect the treatment status of school-aged survey respondents. Second, we run separate regressions for locust swarms and bands. The latter are correlated with a more localized impact of locust outbreaks on individual school dropout, as the movement of wingless locust bands is more limited than that of flying swarms. Third, we restrict the sample to locust-affected countries only and find no qualitative differences from the baseline estimates. Finally, to rule out concerns that our results might be driven by undersampled DHS survey locations, we restrict the estimation sample to observations with at least 5, 10, 20, 30, 40, and 50 individuals within DHS survey locations.

We then examine plausible mechanisms that favor the negative income shock hypothesis. In the first exercise, we use DHS data on country-specific relative household wealth status (poor, middle, and rich) to examine how exposure to locust infestations is mediated by household wealth. We find that school-aged children from poorer households are more negatively affected by past locust infestations than children from wealthier households, highlighting the mediating role of income in pest outbreaks. Second, we show that the estimated effect sizes of locust infestations on individual school dropout probabilities are more pronounced for school-aged children from farming households with large farms ($>$ 5 hectares). This finding is consistent with the tendency of land-abundant households to remove children from school to cope with catastrophic crop yields and income loss following locust outbreaks.

Our results have several important policy implications in the context of rising global temperatures, especially for locust-prone African countries. To explore these implications, we study the relationship between the occurrence of locust infestations and various ecological indicators (e.g., temperature, rainfall, and soil conditions) at the level of small, equally sized grid cells of 0.25 decimal degrees (DD) latitude$\times$longitude over the period 1985 to 2020. Based on this information, we calculate the impact of a permanent 1.5 $^{\circ}C$ temperature rise on the number of months of locust infestation per year and derive possible implications for years of education. We provide evidence of a significant reduction in accumulated years of education of about 1.2 years over the next decade due to climate change.

Furthermore, our findings are relevant to ongoing discussions on family resources and academic outcomes in the context of climate-related shocks in agricultural locust-prone African countries. We contribute to this literature in several ways: First, we consider the effect of recurrent pest shocks on the probability of staying in school. Previous studies focused on the analysis of individual countries and short-term episodes of locust infestation (De Vreyer et al., 2015; Conte et al., 2021). In contrast, we consider cross-country and temporal variation in infested areas. Second, we provide new insights into the impact of locust occurrence on socioeconomic outcomes of farmers who are directly exposed and vulnerable to locust events. The existing economic literature on desert locusts does not clearly distinguish between agricultural and non-agricultural households. Examining the separate and joint effects of locusts on school enrollment for various levels of household wealth is our main contribution to the field of research.

The remainder of the paper is structured as follows. Section 2 outlines the relevant literature on weather and pest-related income shocks and highlights what is novel about our approach and contributions to the existing literature. Section 3 describes the data and key variables used for the analysis. Section 4 presents the empirical strategy. Section 5 discusses the main results, robustness tests, and possible mechanisms. Finally, Section 6 concludes.

2 Relevant Literature

Adverse income shocks and family resources have been identified as key determinants of educational outcomes (Hanushek, 1995; Glewwe and Kremer, 2006; Bogliacino and Montealegre, 2020). Although the literature has investigated the role of income shocks on schooling decisions, it has been largely silent on the impact of locust infestations. Desert locust infestations are unique, given their catastrophic effects on crop yield throughout human history (DLIS, 2020). In addition, good weather and successful cultivation of crops are vital for agricultural production. Since agriculture provides a higher average share of household production in Africa than in other regions of the world (McGuirk and Burke, 2020), it seems plausible that adverse shocks to agricultural productivity could negatively affect real income across households on the African continent.

This paper contributes to the literature on the effects of household resources on educational investments and outcomes. Previous studies have shown that financially volatile households tend to withdraw children from school or reduce the amount of household income allocated to education when money is tight and when the expected returns on education are low. For example, Edmonds (2006) demonstrated that pension transfers are associated with increased education and reduced hours worked for children in households of those receiving the pensions. Dung (2013), in contrast, concludes that negative crop shocks reduce the amount of time children spend doing homework and studying. Furthermore, Brown and Park (2002) found that children from low-income families are three times more likely to withdraw from school, with poor-performing girls dropping out in earlier grades than poor-performing boys. Chen (2015) also found that delayed enrollment in primary school harms children's educational outcomes, with more severe effects on boys. While their findings are inconsistent with those of previous studies, they explained that this may stem from the lack of access to pre-primary education and other parental demographics. In these poor areas, primary education delays reduce the likelihood of enrolling in and completing middle school.

Our paper differs from previous studies in that it focuses on rural responses to large-scale recurrent shocks. Whereas much of the existing literature has focused on one-time shocks (e.g., due to anticipated pension income), our focus is on recurrent shocks: in particular, the effects of both short-term and long-term exposure to locust shocks on schooling. Since some previous studies on this topic were conducted in urban areas of developed countries, where basic public infrastructure and a functioning financial system are available to the broad population, the mechanisms may not be generalizable to rural regions of developing countries.[1] In recent years, researchers have shifted their attention to household resources and educational investment decisions in developing countries, focusing on the population of rural and economically remote areas. With low income

[1]See Ermisch and Francesconi (2000), who used the British Household Panel Survey (BHPS) data (1991-1997) and a sibling difference estimator to estimate the link between parental employment and children's educational attainment in childhood and young adulthood. The results show that educational attainment increases with family income.

and only a few resources that could serve as a cushion (Zamand and Hyder, 2016), this population is relatively prone to income shocks from various sources, such as weather events (Dedehouanou and McPeak, 2019; Afifi et al., 2013) and pest infestations (Conte et al., 2021; De Vreyer et al., 2015). These studies have examined the impact of exogenous income shocks on the school decisions of households in developing economies, producing contrasting results.

Although climate change has beleaguered farmers worldwide, African regions are particularly vulnerable to rainfall and drought. Marchetta et al. (2018) and Björkman-Nyqvist (2013) found that negative precipitation deviations in Uganda and Madagascar diminish the likelihood of school attendance and push young adults into the labor market, with a more significant impact on poor families and young women. Similarly, Kazianga (2012), using data for rural Burkina Faso, found that past income shocks have a significant and adverse impact on current and cumulative years of education, even if these shocks do not materialize in the future. Variations in household income due to deviations in rainfall from its historical mean affect school enrollment and student achievement test scores as a consequence of reduced income.[2] Furthermore, severe environmental shocks affect the quantity and quality of children's education in poor households by causing children to be withdrawn from school, pushed into the labor force, or delayed from school enrollment. A multiplier process initiated by a decrease in community economic activity due to crop shocks could decrease household income further (Dung, 2013). While these studies exploit weather-induced shocks to study how income variation affects individual schooling outcomes, we add to the existing literature by focusing on pest infestations. Locust infestations affect educational decisions solely through the channel of household income, and have no direct effect on school outcomes.[3]

Additional studies have shown that shocks affecting crop production significantly impact the educational investment decisions of households engaged in farming activities (Afifi et al., 2013; Newman and Tarp, 2020). Children from poor households are among the most vulnerable to adverse economic or environmental shocks. Families with a limited capacity to cope with such shocks are more likely to pull children out of school to join the work force or to delay children's entry into school. Findings suggest that households can in some cases smooth income and consumption by selling off livestock, but the depletion of assets (e.g., livestock, land, grain stocks, and farm equipment) from past exposures causes crop income to decrease significantly, leaving households worse off in the long term (Carter and Lybbert, 2012; Kazianga and Udry, 2006; Barrett et al., 2006).

Whereas existing studies focus on single countries[4], we extend the literature by focusing on a large number of African countries with a history of severe locust infestations. We also contribute to the research on the effects of shocks caused by pest infestations. In contrast to previous studies on this topic, we use a broader

[2] For example, through a reduction in educational expenditures on children's textbooks, class fees, etcetera.

[3] See Zimmermann (2020), who revealed that negative rainfall shocks have an increasing positive impact on school enrollment over time and *vice versa*. This is because after a positive rainfall shock, children may have to leave school when employment is available but be able to continue their education when jobs are hard to come by.

[4] See De Vreyer et al. (2015) for the impact of locust plagues on educational outcomes in Mali.

geographical coverage and a meticulously implemented empirical methodology. In addition, we select carefully from the set of control variables that might confound the relationship between individual schooling and locust shocks (e.g., bio-geographic, climatic, and socio-demographic factors). Moreover, we study heterogeneous effects of locust shocks on individual school outcomes in farming and non-farming households and provide an exhaustive set of sensitivity tests to examine the robustness of our main findings.

3 Data and Variables

3.1 Demographic and Health Surveys (DHS) Program

The household survey data used in this study come from the Demographics and Health Surveys Program (DHS, 2021), a systematic study of individuals in developing countries. The DHS program provides individual-level data on 32 African countries that are relevant to this study. The main topics cover the health, nutrition, living arrangements, and socio-demographics of the respective populations. The data consist of a repeated cross-section; that is, countries are sampled repeatedly but with a different survey population each time. The general structure of the survey is that several survey locations[5] are chosen for each country and wave. The locations are comprised of multiple households, which in turn contain multiple individuals. While the DHS dates back to 1990, only the data sets since 2005 are relevant to the present study, as they provide geo-coded information on the survey location and farming status of each household. This feature enables us to link the survey data to other geo-coded datasets to complement the survey data with additional information on local living conditions.

Throughout the empirical analysis, we use individual schooling status, that is, whether or not a respondent is currently enrolled in school. We restrict the sample to the population aged 3 to 24 years to cover the various levels of education, ranging from pre-primary for ages 3 and above to post-secondary or tertiary education for ages up to 24 years. The age range further allows us to account for grade repetition, as we also capture students with a high age relative to their current grade. Through the definition of our measure, more than half of the individuals in our sample are currently enrolled in school.[6]

We use information on whether survey respondents own land used for agricultural purposes to identify households as farmers. Initially, we classify households that do not own or cultivate agricultural land as non-farmers and all others as farmers. Similar to the resource curse hypothesis, we expect that the high pervasiveness of agricultural employment in the population entails a lack of incentives for educational investment decisions (Sachs and Warner, 2001; Easterly and Levine, 2003). As an extension of this approach, we differentiate between small (up to 2 hectares), medium (3 to 5 hectares), and large farmland owners (more than 5 hectares).[7]

[5]In the DHS program, these are referred to as "clusters". In the scope of this study, we prefer the term "survey locations".

[6]See the summary statistics presented in Table A4 in the Appendix for additional details on the composition of the regression sample.

[7]We borrow from the definition used by the World Bank (2003) to classify small farmland owners.

In addition, we control for different household-level determinants that relate to educational investments. These include the educational level of the household head, as higher education is correlated with better occupational opportunities and higher income, which might benefit a child's educational outcomes (Ermisch and Francesconi, 2000). The level of education of the parents or guardians can affect the optimal allocation of resources to educational investment. For example, educated parents or guardians might provide better support for their children's education, helping with homework and giving advice on the choice of school subjects, and serving as role models and encouraging the pursuit of schooling and higher education. To further control for the family structure and the household's living arrangements, the individual's relationship to the household head is included.

The gender of the household head and individual is also included (Coulibaly et al., 2015). Controlling for an individual's gender is essential, for instance, if educational returns differ by gender through differential treatment at home and school or if labor market conditions vary by gender.[8]

Finally, we use survey information relating to household possessions, material resources, and access to public infrastructure. Household possessions can affect an individual's schooling status, as they indicate the ability to purchase goods and services that are complementary to education (e.g., food, health services). Furthermore, car ownership is a measure of wealth, mobility, and access to the road network. Moreover, we control for the type of building materials used in the home to consider the poverty level of households.

3.2 Exposure to Locust Infestations

The main explanatory variable considered in this study is the spatial data on locust swarms and bands. The geocoded data are from the Food and Agriculture Organization and are published by the Desert Locust Information Service database. The data have been collected since 1985 and are available for all infested areas worldwide.[9] All records are provided with the exact date (day, month, and year) for events between 1985 and 2020.

For the individual locust infestation events, only a point location, and for a limited sample, the affected area (which measures the degree of intensity at a localized level) is given, so the exact spread or flight patterns are not observed or recorded. Accordingly, the spatial extent of the infestations must be approximated using spatial buffers around the locust point location. Desert locust swarms can travel vast distances of about 150 km and can fly for up to 10 hours a day downwind, so they can spot acres upon acres of cropland and forage to consume. As an illustration, they can cover a distance between Rome to Paris (about 1,000 km) within one week (FAO, 2022). Given this information, we initially use a buffer size of about 50 km around a DHS survey

[8] Female students have been found to be more likely to withdraw from school than males (Björkman-Nyqvist, 2013).

[9] According to reports by the United Nations Environment Programme (UNEP), during quiet periods known as recessions, desert locusts are normally restricted to the semi-arid deserts of Africa, the Near East, and South-West Asia – areas that receive less than 200 mm of rainfall annually. These areas span about 16 million km^2, comprising about 30 countries. During plagues, however, desert locusts may spread over 29 million km^2, extending over or into parts of 60 countries (FAO, 2009). In the face of ongoing climate change, warmer temperatures could cause locusts to multiply more rapidly. Hotter weather and geographic differences in desert locust breeding and feeding areas also mean that other areas are not immune from infestations (Piou et al., 2019).

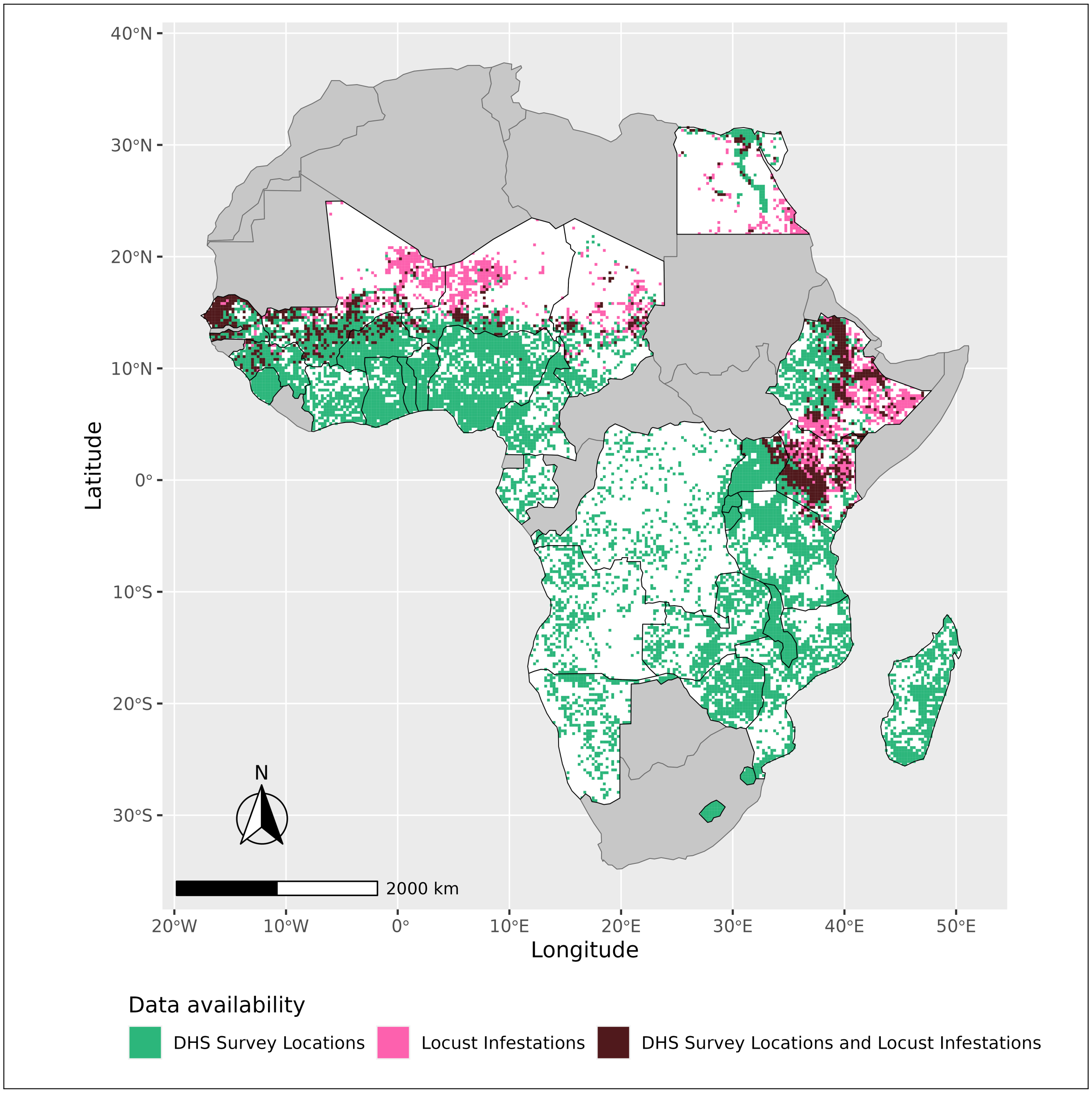


Figure 1: Spatial Distribution of DHS Survey Locations and Locust Infestations

Notes: This map visualizes the spatial distribution of the DHS survey locations and locust infestations. Locust infestations include both locust swarms and bands. For better visibility, the data are aggregated to rectangular grid cells of 0.25 decimal degree (DD) size. Countries that are part of the sample are highlighted. See the main text for additional details.

location.[10]

Desert swarms have the unique ability to induce behavioral, color, and shape changes within a few hours in response to a change in their population density (Song et al., 2017), thereby increasing the rate at which they consume plant materials (Chen et al., 2020). At low numbers, locusts are solitary, but as densities increase, they become gregarious and remain together in dense swarms of adults and bands (immature locusts with

[10]This corresponds to an area of about 7,852 km^2. In the empirical analysis, we examine the sensitivity of the baseline findings to the definition of smaller buffer sizes.

no wings, also known as hoppers) (Lomer et al., 2001; Collett et al., 1998). Plagues occur when locusts reproduce frequently and successfully for one to several years. This enables numerous swarms to form and invade agricultural land and food areas (Zhang et al., 2019; Healey et al., 1996).

Figure 1 shows the African countries that constitute our regression sample and the spatial distribution of the household survey locations and locust infestation events employed. Countries that are part of the sample are highlighted.[11] For clarity of presentation, the data are aggregated to rectangular grids of 0.25×0.25 decimal degree (DD) size.

The fill color of the grid indicates whether the grid cell contains only DHS survey locations (medium green), locust swarms or bands (light pink), or both DHS survey locations and locust swarms or bands (dark red). Locations at which the DHS survey has been conducted cover the entire area of the respective countries, with a focus on the more densely populated areas. It is evident that the occurrence of desert locust swarms and bands is relatively concentrated within a belt slightly north of the equator (between approximately 15 degrees north and 5 degrees south) and in Egypt in the North.

Consequently, only some of the reported locust swarm or band locations are geographically close to DHS survey sites. For example, in Mali, a large share of locust infestations are in the sparsely populated northern part of the country, whereas most survey locations are in the South. Furthermore, some countries included in the sample are made up predominantly of rural areas but have been unaffected by desert locust invasions so far. These include Ghana, Togo, the Democratic Republic of Congo, and Gabon. We include these countries nevertheless to ensure a regression sample that is representative of central African countries, but also provide robustness analyses for their omission.

3.3 Spatial Matching Approach

The spatio-temporal matching approach for our data is illustrated in Figure 2, based on survey locations from the 2006 DHS conducted in Mali and the country's locust infestations. The inset map in the upper right part of the figure shows the spatial distribution of DHS locations and locust events across the entire country, whereas the main map shows the rural area of northern Mali indicated by the red rectangle in the inset map.

The main map shows three survey locations (A, B, and C, each indicated by a triangle) that were part of the 2006 DHS survey. For orientation purposes, the main road types and the locations of villages or settlements are shown. The sparse road network and the dispersed distribution of villages or settlements underscores the rural character of the area. For each of the survey locations, the 50 km buffer is represented by the surrounding circle. Locust infestations are visualized by dots, where a solid red fill represents events relevant to our study that fall within a 50 km distance around DHS locations and maximum time lag of 120 months prior to the survey interview date. Dots characterized by a light red fill represent locust infestations that occurred within 120 months but outside a range of 50 km around any survey location. Finally, colorless dots represent locust infestations dating back more than 120 months, which are accordingly not relevant to our study, regardless of

[11] See Table B2 in the Appendix for a detailed description of the countries and survey waves included.

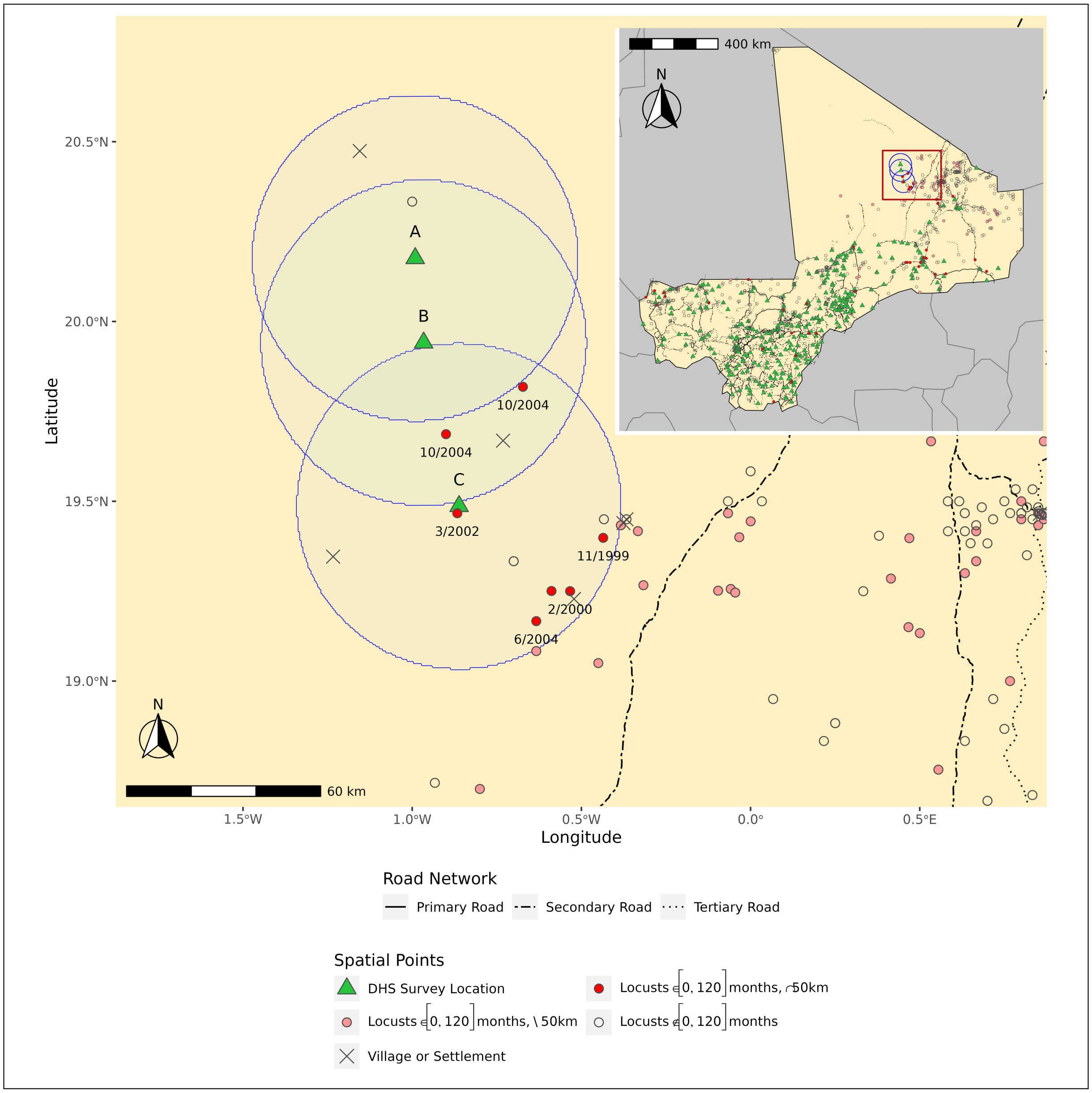


Figure 2: Illustration of the Spatial Matching Approach Between Locust Events and DHS Locations in Mali

Notes: This map illustrates the spatio-temporal matching approach of DHS survey locations and locust occurrences. The main map shows a selection of an area of Mali ranging from $1°45'W$, $18°45'N$ to $0°45'E$, $20°45'N$. See the main text for further details.

whether they are located within 50 km distance range of the DHS locations.

Out of the three survey locations, DHS location A has only one locust infestation within 50 km range, which, however, lies more than 120 months in the past and is therefore not relevant to the empirical analysis. Following this, households that are part of DHS location A are considered not affected by locust infestations. DHS location B has two proximate locust infestations, both of which occurred in October 2004. As these infestations fall within the 50 km range and 120 months' time, DHS location B is considered as affected by locust infestations. For this location, the count of infestations equals two, whereas the number of affected months is one. For DHS location C, a total of seven locust infestations are located inside the 50 km buffer and date back no longer than 120 months. Two additional locust infestations are within 50 km but occurred more than 120 months in the past. Note that the two infestations from October 2014 are relevant for both DHS locations *B* and *C*. Accordingly, the count of locust infestations for location *C* is seven, whereas the number of affected months is six.

3.4 Additional Geospatial Controls

We complement our data with a set of local characteristics related to geography, climate, population, and economic activity to control for possible omitted factors that could affect the exposure to locust infestations and educational outcomes. If not otherwise stated, we employ one year lag averages of monthly observations among the set of time-variant controls around DHS locations throughout the empirical analysis.

Nighttime light intensity. We follow the relevant literature and use satellite-measured nighttime light time series data to capture the extent of economic activity at the local level (Chen and Nordhaus, 2011; Addison and Stewart, 2015). Even though GDP is often preferred as a measure of economic activity, it is more aggregated and often suffers from measurement error problems (Henderson et al., 2012).

We combine luminosity data from two main sources to obtain longer time series data: (i) the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Centre (NGDC) (NOAA-NGDC, 2015), (ii) and the Visible Infrared Imaging Radiometer Suite (VIIRS) (Elvidge et al., 2021). Luminosity data from the first source were collected by the US Air Force Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). At the same time, the latter is a joint NASA/NOAA Suomi National Polar-orbiting Partnership (Suomi NPP) collaboration. The DMSP-OLS and VIIRS luminosity data differ in a series of technical characteristics for artificial light detection in terms of spatial resolution, dynamic range, measurement, calibration, and temporal frequency (e.g., yearly versus monthly data collection) (Elvidge et al., 2013).

We use the method of inter-annual calibration to rescale luminosity data from the various satellite nighttime light observations to the data range of the DMSP-OLS F12 series using 1999 as the reference year and Los Angeles as the reference area (Elvidge et al., 2009, 2014). Nighttime light activity is measured by a digital number (DN) value ranging from 0 to 63, where higher values indicate more light emissions.

We aggregate the luminosity data to equally sized grid cells of 0.1×0.1 DD grid size. The resulting measure is then spatially joined to DHS survey locations based on the respective latitude and longitude coordinates. In our empirical analysis, we control for the 12 month average nighttime light intensity at the DHS survey location.

Conflict events. The Uppsala Conflict Data Program (UCDP) Georeferenced Event Dataset (GED) provides geographically and temporally highly disaggregated data on individual conflict events for the post-1989 period (Sundberg and Melander, 2013). We calculate the number of conflict events across 0.1 DD grid cells and match the resulting outcomes to DHS survey locations. Thus, we consider that local conflict events might negatively impact schooling outcomes. Long-term conflict events reduce the average years of education and literacy rates, and leave a smaller population with formal education (UNESCO, 2010). Some locust-infested areas such as Ethiopia and Mali experienced some form of civil unrest in the period used for our analyses. To rule out potential concerns that our estimates might be prone to differences in conflict patterns across regions within countries, we control for the total number of conflict events up to 12 months prior to the DHS survey date.

Population. We use data on total population counts using the Gridded Population of the World database, Version 3 and 4 for the years 1990-2020 with five-year intervals (CIESIN-FAO-CIAT, 2005; CIESIN, 2018), to rule out the possibility of population growth with increased school attendance/enrollment. We employ a simple linear interpolation between each five-year interval to construct a global population count grid time series estimate for 1990 to 2020. We then calculate the total population count estimate within 0.1 DD grid cells and assign that value to the respective DHS locations. Again, we consider the average population count value 12 months prior to the DHS survey date.

Climate conditions. Monthly data on temperature, precipitation, and potential evapotranspiration is taken from the Climate Research Unit Time Series dataset (CRU TS Version 4.05) with a spatial resolution of 0.5 DD grid size (Harris et al., 2020). In addition, we use monthly data on severe drought episodes based on a 12-month time scale Vicente-Serrano et al. (2010). The corresponding Standardized Precipitation Evapotranspiration Index (SPEI) is included. Negative values indicate severe drought episodes relative to the fixed time scale of 12 months. Successful cultivation of crops largely depends on climate conditions. Severe droughts or floods have devastating effects on farming household income, leading to a reduction in school enrollment (Björkman-Nyqvist, 2013). The inclusion of climate controls in the empirical analysis addresses potential concerns due to the confounding effects of climate conditions and the endogenous formation of large locust plagues. For all climate controls, we choose a lag length of 12 months and take the mean value for this period.

Geography controls. We consider a complete set of distance-based controls from the location of DHS survey location sites to the country's border, coastline, major river, largest settlement (i.e., population $> 100,000$ in the year 2000), historical Christian missions, railroads, and road lines. Moreover, we construct grid cell-specific indicators of land suitability for agriculture (0.5 DD grid size) and agricultural land coverage (with a cell-level resolution of 0.1 DD) (Ramankutty et al., 2002, 2008). In addition, we process high-resolution elevation data to capture local topographic conditions taken from the Shuttle Radar Topography Mission (SRTM), version 2.1, with a spatial resolution of 3 arc seconds (approximately 90 meters at the equator) (NASA JPL, 2013). We aggregate the data by calculating the mean and standard deviation of elevation measures (in meters above sea level) within 0.1 DD grid cells. In the empirical analysis, we assess the confounding effects of geography controls on the relationship between school dropouts and locust infestations.

4 Empirical Strategy

4.1 Identification Strategy

The geographic information available for both the sites of locust infestations as well as the survey locations of the DHS data set allows us to identify treated DHS locations and non-treated locations based on the construction of different buffer sizes around the DHS locations and the timing of locust events. We base our empirical strategy on the following treatment specification:

$$N_{dct(\tau)}^{\bar{b}km} = \sum_{l \in L_d^{\bar{b}km}} LocustEvent_{ls}^{\bar{b}km} \times \mathbb{1}(t - s = \tau), \tag{1}$$

where $N_{dct(\tau)}^{\bar{b}km}$ counts the number of locust events within distance $\bar{b}$ around DHS location d of country c that were observed $\tau = \{1, 2, \ldots, \overline{m}\}$ months prior to the DHS interview date t[12], $L_d^{\bar{b}km}$ is the set of locust events $\bar{b}$ km around DHS location d, and $LocustEvent_{ls}^{\bar{b}km}$ is a binary indicator of locust event l at time s within a $\bar{b}$ km distance around DHS location d. We consider all locust events up to $\overline{m}$ months prior to the survey date of DHS location d. We use information on the DHS survey date t and the approximate time of locust infestations s to select among the most important locust events around DHS locations. Accordingly, locust infestations that have occurred more than $\overline{m}$ months in the past or that have occurred outside the $\bar{b}$ km buffer range are regarded as irrelevant to survey respondents at the respective DHS survey location.

We focus on infestations within a 50 km buffer and a maximum time lag of 120 months prior to the DHS survey date. We choose this approach because of the flight duration and randomness of locust events. Locust swarms fly with an approximately downwind trajectory for distances of up to 150 km per day (DLIS, 2020). Since DHS locations do not represent the exact location of the household members due to geographical displacement, the choice of buffer size is critical. This and the choice of time lag present a trade-off between the number of infestations and treated locations. A larger buffer size, for instance, increases the noise, that is, the likelihood of counting individuals who were not affected by locust shocks. In addition, a shorter time lag would risk overlooking locust events that are still exerting an impact on current school enrollment status due to the effect of past school interruptions. To address this concern, we provide estimates with different buffer sizes and time lags.

Based on Equation (1), we construct a binary locust treatment indicator of infested months rather than the count number of locusts events. In this regard, we examine the *extensive margin* instead of the *intensive margin* of locust events within a maximum time lag of 120 months and the resulting consequences on individual schooling decisions.[13] Thus, we consider the following slightly modified treatment indicator:

$$M_{dct(\tau)}^{\bar{b}km} = \mathbb{1}\left(N_{dct(\tau)}^{\bar{b}km} > 0\right), \tag{2}$$

[12]For each DHS location, we retrieve the corresponding survey year and month.

[13]Thus, we are interested how the mere presence of locust events in a given month affect school enrollment rather than the total number of locust events. We argue that a single locust event can be so severe that it destroys crop yield in a month, while subsequent events might have a negligible effect on household educational decisions.

where $M_{dct(\tau)}^{\bar{b}km}$ takes a value of 1 if a particular DHS location was subject to at least one locust event τ periods prior to the DHS survey date, and zero otherwise. Provided that there are differences in the effect of locust infestations on schooling relative to the timing of these shocks, we create bins that count the number of months of locust infestations that fall within the following time range prior to the DHS interview date: $x \in \mathbb{A} = \{[1-24],[25-48],[49-72],[73-96],[97-120]\}$, such that $CM_{dct(a)}^{\bar{b}km} = \sum_{\tau=24(a-1)+1}^{24a} M_{dct(\tau)}^{\bar{b}km}$ counts the number of months of locust infestations in each time bin $f(x) = a \in \mathbb{B} = \{1,2,3,4,5\}$, where $f : \mathbb{A} \mapsto \mathbb{B}$. Note that we assume no effect of locust shocks that occurred more than 10 years ($>$ 120 months) prior to the DHS interview date on current school enrollment status. We think that 120 months prior to the DHS interview date is long enough to identify any effect of locust exposure on school outcomes. Longer time lags would risk blurring the effects of exposure to locust shocks on schooling because of a relatively long period of recovery from such shocks.[14]

We strengthen our identification strategy by identifying and assigning those locust events to DHS respondents who were of school age at the time of the survey (between 3 and 24 years old). The DHS program provides the age of the survey respondents in all survey rounds. Given this information, we consider different bins of locust exposure depending on the age of the survey respondents in periods that might have an impact on school enrollment status during locust infested months. For example, children who were 7 years old at the time of the DHS interview are regarded as treated by locust events observed in the past 5 years, as this period of exposure is long enough to see an effect on school outcomes, but short enough to exclude locust events that do not affect children of (pre-)school age (i.e., age < 2). We construct age-specific treatment indicators by interacting the different time bins that count the number of months of locust infestation with the addition of an interaction term $\mathbb{1}(Age_{idt(\tau)} \geq 2)$ that takes a value of 1 if individual i sampled from DHS location d was at least 2 years old (i.e., the year before entering pre-school) τ periods prior to the DHS interview date t, such that:

$$TM_{idct(a)}^{\bar{b}km} = \sum_{\tau=24(a-1)+1}^{24a} M_{dct(\tau)}^{\bar{b}km} \times \mathbb{1}(Age_{idt(\tau)} \geq 2). \tag{3}$$

Relying on this definition of the treatment status of school-aged children ensures that we only count locust infestations that are relevant to the relationship between current school enrollment status and observed locust shocks. Thus, we deliberately exclude time-distant locust shocks that were not directly linked to school-aged survey respondents, as such shocks occurred at a time when the individual was not born.

[14]Nevertheless, we provide additional estimates to different time lag specifications when we study dynamic effects of locust infestations on school enrollment.

4.2 Descriptive Statistics

This section provides descriptive statistics of the main variables used in the paper, differentiated by treatment (total, treated, and non-treated sample),[15] farming type, and age group. Overall, the data suggest that the majority of farming households are involved in large-scale farming; in total, about 46% of individuals belong to households with sizable farms (see Table A4 in the Appendix). For these households, locust outbreaks are likely to result in severe income losses. After a locust infestation, farming households also need extra labor (e.g., to replant or save crops), which is often provided by children in the time they would otherwise spend in school. Furthermore, the destructiveness of locusts means that income loss of this scale is likely to have long-lasting effects on households' capacity to smooth consumption. Another data observation is that agriculture is a dominant activity in these areas for both treated and non-treated farming households.

The dynamics of household farming types can be seen in our data. For the most part, in Table 1 Panel (A), which refers to all households without the distinction between household types in our sample, schooling decisions differ slightly between treated and non-treated households. When splitting the sample by farming type, we observe a more apparent distinction between farmers and non-farmers. Panel (B) reveals that members of farming households are, on average, characterized by a lower probability of school enrollment and a lower number of years of schooling than treated non-farmers (shown in Panel (C)).

There is a significant difference when we further differentiate between the treated and non-treated sample. In the treated sample, farming households show significantly lower levels of education than non-farmers. Households that are not engaged in farming activities have two more years of education than farmers. Both Panels (B) and (C) support our theory that locust outbreaks may seriously influence agricultural households' decisions about sending their children to school.

To demonstrate the patterns and dynamics of locust infestations, we supplement the studies with summary statistics broken down by age groups. Our treated households enroll their children in school five years later than non-treated households (as early as three years, see Table A2 and A3). We can infer that locust shocks may cause a delay in school enrollment. Table A2 shows that, on average, older age groups (15 to 24 years old) have a lower likelihood of attending school than younger age groups (3 to 14 years old). However, years of education are similar between treated and untreated samples (see Table A3). The number of times an individual is affected by locusts also rises with age. By construction, younger individuals are more likely to be affected by recent events (1-48 months) than by events further in the past. At the same time, older individuals display a combined effect of current and past locust shocks.

[15]Treatment refers to individual-specific exposure to any locust infestation within the 120 months prior to the survey date. Individuals who experienced at least one locust-infested month are considered as *treated*, while all others are considered *non-treated*.

Table 1: Descriptive Statistics for the Main Regression Variables by Treatment and Household Farming Status

	Total Sample				Treated Sample				Non-Treated Sample			
Variables	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
	Panel A: All Households											
Years of Schooling	3.094	3.681	0	24	4.086	4.148	0	24	3.006	3.624	0	24
Currently in School	51.344	49.982	0	100	49.723	49.999	0	100	51.488	49.978	0	100
$TM^{\overline{50km}}_{idct[f(1-24)]}$	0.019	0.195	0	5	0.230	0.645	0	5	0	0	0	0
$TM^{\overline{50km}}_{idct[f(25-48)]}$	0.027	0.243	0	4	0.337	0.789	0	4	0	0	0	0
$TM^{\overline{50km}}_{idct[f(49-72)]}$	0.016	0.155	0	3	0.194	0.510	0	3	0	0	0	0
$TM^{\overline{50km}}_{idct[f(73-96)]}$	0.048	0.346	0	6	0.591	1.072	0	6	0	0	0	0
$TM^{\overline{50km}}_{idct[f(97-120)]}$	0.063	0.426	0	8	0.773	1.296	0	8	0	0	0	0
	Obs.: 2,217,852				Obs.: 180,796				Obs.: 2,037,056			
	Panel B: Farming Households											
Years of Schooling	2.707	3.370	0	24	2.944	3.480	0	19	2.691	3.362	0	24
Currently in School	51.344	49.982	0	100	49.723	49.999	0	100	51.488	49.978	0	100
$TM^{\overline{50km}}_{idct[f(1-24)]}$	0.014	0.167	0	4	0.217	0.617	0	4	0	0	0	0
$TM^{\overline{50km}}_{idct[f(25-48)]}$	0.015	0.183	0	4	0.223	0.681	0	4	0	0	0	0
$TM^{\overline{50km}}_{idct[f(49-72)]}$	0.016	0.154	0	3	0.239	0.554	0	3	0	0	0	0
$TM^{\overline{50km}}_{idct[f(73-96)]}$	0.047	0.342	0	6	0.709	1.148	0	6	0	0	0	0
$TM^{\overline{50km}}_{idct[f(97-120)]}$	0.050	0.400	0	8	0.763	1.380	0	8	0	0	0	0
	Obs.: 1,534,928				Obs.: 100,636				Obs.: 1,434,292			
	Panel C: Non-Farming Households											
Years of Schooling	3.961	4.170	0	24	5.517	4.462	0	24	3.755	4.085	0	24
Currently in School	54.817	49.767	0	100	56.307	49.601	0	100	54.619	49.786	0	100
$TM^{\overline{50km}}_{idct[f(1-24)]}$	0.029	0.245	0	5	0.246	0.678	0	5	0	0	0	0
$TM^{\overline{50km}}_{idct[f(25-48)]}$	0.056	0.340	0	4	0.481	0.885	0	4	0	0	0	0
$TM^{\overline{50km}}_{idct[f(49-72)]}$	0.016	0.158	0	3	0.137	0.442	0	3	0	0	0	0
$TM^{\overline{50km}}_{idct[f(73-96)]}$	0.052	0.354	0	6	0.443	0.947	0	6	0	0	0	0
$TM^{\overline{50km}}_{idct[f(97-120)]}$	0.092	0.478	0	8	0.787	1.183	0	8	0	0	0	0
	Obs.: 682,924				Obs.: 80,160				Obs.: 602,764			

Notes: This table presents descriptive statistics for all individuals in the sample in both the treatment and non-treatment group. *Currently in School* refers to individuals between 3 to 24 years of age who are still in school at the date of the DHS interview. It is scaled to 100, that is, 0 when the individual reports not being in school and 100 for being in school. See Table B1 in the Appendix for further information on variables definition and sources.

4.3 Estimation

To examine the impact of locust-related shocks on individual school outcomes among farming and non-farming households, we estimate the following regression equation:

$$y_{ihdct} = \sum_{a\in\mathbb{B}} \beta_1^a TM^{\overline{50km}}_{idct(a)} + \beta_2 Farmer_{hd} + \sum_{a\in\mathbb{B}} \beta_3^a \left(TM^{\overline{50km}}_{idct(a)} \times Farmer_{hd} \right) + \mathbf{X}'_{ihdt}\theta + \mathbf{Z}'_{dt}\delta + \mathbf{G}'_{d}\phi + \varepsilon_{ihdct}, \quad (4)$$

where y_{ihdct} is an indicator variable that equals 100 if the respondent i is currently enrolled in school, in household h, living in DHS location d, in country c, and time t, and zero otherwise. $Farmer_{hd}$ is a binary indicator that equals one if individual i belongs to a household h engaged in farming activities, and zero otherwise. The vector $\mathbf{X}'_{ihdt}$ contains a standard set of individual and household-level controls (e.g., age, gender, and household head characteristics), which do not suffer from the "bad controls" problem (Angrist and Pischke, 2009). The vector $\mathbf{Z}'_{dt}$ contains time-variant demographic, socioeconomic, and climatic controls for DHS location d in country c at time t, and $\mathbf{G}'_d$ is a vector of time-constant geographic controls.

The main coefficient of interest β_3^a captures the impact of locust-related shocks depending on the farming status of the household across the different time bins $a \in \mathbb{B} = \{1,2,3,4,5\}$. Specifically, we test whether an agricultural household is affected more negatively by a locust event than a non-farming household. The identifying assumption is that locust-related shocks affect individual schooling outcomes through their effect on agricultural activities. We find this assumption plausible, as severe losses of agricultural production accompany locust-related shocks.[16] Finally, ε_{ihdct} is an idiosyncratic error term. Unless otherwise stated, the standard errors are clustered at the DHS location level d throughout all regressions.

We augment Equation (4) with a large set of regional and time fixed effects to control for differences in school enrollment status across regions and time. First, we interact first-order administrative regions with DHS survey year and month $\lambda_{dcrt(y,m)}$, where $t(y,m)$ denotes the year and month of the time variable t. This allows us to flexibly control changes in child school enrollment status over time due to, for example, differences in the expansion of schooling services across time and within regions, and seasonal variation of child school enrollment status due, for example, to differences in agricultural harvesting cycles and academic calendars in different regions of a country. The inclusion of $\lambda_{dcrt(y,m)}$ interacted with first-order administrative regions leaves some spatial variation by comparing children of school age who were interviewed in the same year and month but located in different locust-affected areas of the same region. It also employs some temporal variation by exploiting information on children of school age who live in the same region of a country but were interviewed in different calendar years and months.

Thanks to the construction of our locust treatment variable, we are able to control for DHS survey location fixed effects. This fixed effects specification only exploits variation across children of school age within the same DHS survey location, where identification comes from children who are differently affected by locust shocks due to differences in the age of the household member at the time of the survey interview. We also include age-of-member fixed effects to flexibly control for a possible non-linear relationship between school enrollment status and age (Chen, 2015; Brown and Park, 2002; Cockburn and Dostie, 2007).

Locust infestations provide a convincing source of quasi-experimental variation in household income for several reasons. First, desert locust infestations do not affect education through channels other than income (such as crop failure). Second, our approach differs significantly from previous approaches that exploit exogenous variation in weather conditions to examine the impact of income shocks on, for example, individual school outcomes. Prior research has not entirely ruled out alternative mechanisms by which weather-related shocks like rainfall variations might affect education in other ways than through changes in household income. For example, there is still the possibility that rainfall could alter schooling decisions by damaging school buildings

[16] We provide a discussion of possible mechanisms in Chapter 5.3 at the end of the empirical analysis.

and road accessibility. Rainfall could also exacerbate diseases such as malaria (by creating breeding grounds for mosquitoes) or affecting individuals' ability to attend school. In contrast, our approach based on locust-related biological shocks as a source of exogenous income variation is not subject to the aforementioned caveats, as it only affects schooling decisions through changes in crops and pasture lands.

In addition, locust infestations offer a degree of variation due to the randomness of their occurrence over time. Due to climate change and the ecological conditions that favor desert locusts, the prevention of infestations is difficult. Hence, not only are these shocks destructive in the labor-intensive context of agricultural production in Africa; infestations also significantly affect crop yield and household welfare.

Another issue is that schooling might be affected by factors other than income. Weather patterns over time might generate differences in household characteristics across regions. For instance, locations with more favorable environmental conditions (e.g., abundant amounts of rainfall for agriculture or an absence of pest-related infestations) might be more populated and have more stable income sources than households with less favorable bio-geographical conditions. These factors may all be correlated with household schooling decisions. Thus, we control for the mean of weather-related variables (e.g., temperature, precipitation, or drought shocks) and other important time-invariant variables.[17]

The locust-specific treatment effects for individuals in farming households across the different time bin categories are represented by the regression coefficient β_3^a, which can be interpreted as the effect on the probability to stay in school of a one unit increase in the number of locust-affected months in each time bin $a \in \mathbb{B}$. Note that the estimated regression coefficients should be interpreted relative to the omitted time bin category, which is > 10 years in our baseline specification. Provided that exposures to locust infestations on schooling are largely reversible in the long run, we should observe a more severe impact on school dropouts in more recent time bins.

5 Main Results

5.1 Effect of Locust Shocks on School Dropout

Baseline findings. Table 2 presents the first results from estimating Equation (4) with a varying set of baseline controls. Throughout all model specifications (1)-(6), we separately control for household farming status and exposure to locust shocks across the different time bins (estimates not shown). Thus, we take into account possible differences in school enrollment status between children from farming and non-farming households. In addition, we control for a possible direct effect of locust exposure on school dropout due, for example, to increased short-run labor demand to help salvage crops when locusts appear on the fields.[18]

[17] In the most restrictive model specification that controls for DHS survey location fixed effects, we provide evidence that our findings are not prone to these kinds of endogeneity problems.

[18] For example, mobilizing labor in the short run might be the cheapest and most convenient way to prevent total crop failure. Farming households might therefore be more likely to alter their children's school attendance in the short run.

Table 2: Locust Infestations and Individual Schooling Outcomes – Baseline Results, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Indicator of Currently Being in School					
$TM^{\overline{50km}}_{idct[f(1-24)]} \times Farmer_{hd}$	0.3521	0.2521	0.3779	0.3528	0.1229	0.1663
	(0.8638)	(0.8883)	(0.9018)	(0.8923)	(0.8706)	(0.8546)
$TM^{\overline{50km}}_{idct[f(25-48)]} \times Farmer_{hd}$	-1.9031***	0.3058	-0.1907	-0.1596	-0.5624	-0.5463
	(0.6723)	(0.6817)	(0.6773)	(0.6762)	(0.6710)	(0.6689)
$TM^{\overline{50km}}_{idct[f(49-72)]} \times Farmer_{hd}$	-4.9390***	-3.3073***	-2.9560***	-2.9335***	-2.5640**	-2.3877**
	(1.1132)	(1.1201)	(1.0915)	(1.1097)	(1.1005)	(1.1216)
$TM^{\overline{50km}}_{idct[f(73-96)]} \times Farmer_{hd}$	-2.1788***	-1.9087***	-1.9787***	-1.9560***	-1.9046***	-1.8101***
	(0.5524)	(0.4501)	(0.4326)	(0.4338)	(0.4309)	(0.4314)
$TM^{\overline{50km}}_{idctf[(97-120)]} \times Farmer_{hd}$	-1.5179***	-0.7470**	-0.7712***	-0.7709***	-0.8796***	-0.7906***
	(0.3656)	(0.2968)	(0.2924)	(0.2921)	(0.2899)	(0.2903)
Observations	2,217,852	2,217,852	2,217,852	2,217,852	2,217,852	2,217,852
Adjusted R^2	0.003	0.085	0.091	0.092	0.093	0.094
Number of DHS Survey Locations	33498	33498	33498	33498	33498	33498
Mean of Dep. Var.	51.34	51.34	51.34	51.34	51.34	51.34
Country×Region×Time FE	No	Yes	Yes	Yes	Yes	Yes
Geographic Controls	No	No	Yes	Yes	Yes	Yes
Land Productivity Controls	No	No	No	Yes	Yes	Yes
Socioeconomic Controls	No	No	No	No	Yes	Yes
Weather Controls	No	No	No	No	No	Yes

Notes: Data are from various DHS survey years in Africa. Observations are at the survey respondent level complemented with household, DHS survey location, and aggregated geo-spatial controls. The dependent variable is a binary indicator of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 3 and 24. $TM^{\overline{50km}}_{idct(a)} \times Farmer_{hd}$ is an age-specific locust treatment indicator that counts the number of months of locust infestations in time bin $a \in \mathbb{B} = \{1,2,3,4,5\}$ prior to the DHS survey interview date interacted with the household's farming status. All regressions control separately for household farming status and the various locust treatment bins. *Geographic Controls* include DHS survey location absolute centroid latitude, absolute centroid longitude, distance to the country's border, coastal river, capital city, largest settlement, Catholic missions, Protestant missions, railroads, and roads. *Land Productivity Controls* include mean land suitability for agriculture, mean cropland coverage, mean pasture land, mean elevation, and standard deviation of elevation. *Socioeconomic Controls* include log mean light intensity, log mean population size, and number of conflict events 1-12 months prior to the DHS survey interview date. *Weather Controls* include mean temperature, mean precipitation, mean potential evapotranspiration, drought intensity, and number of frost days 1-12 months prior to the DHS survey interview date. $Country \times Region \times Time\ FE$ are fixed effects of the calendar year and month of the country's region according to the DHS data. See the main text for additional details on data construction and sources. Clustered standard errors by DHS survey location level are shown in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

If locust infestations reduce agricultural production, we expect such shocks to mediate the extent of crop failures on individual school dropouts. We test this hypothesis by interacting the locust events variable $TM^{\overline{50km}}_{idct(a)}$ with $Farmer_{hd}$, our binary indicator for individuals belonging to farming households. The regression coefficient on the interaction term corresponds to the effect of locust infestations on individual school enrollment status for individuals living in farming households.

Column (1) presents regression estimates without controls. The results indicate that individual school dropout is amplified for individuals belonging to farming households. For example, the regression coefficient of -1.9031 for the second time bin implies that a single monthly locust event during a period of three to four years prior to the DHS survey date would, ceteris paribus, increase the probability of individual school dropout by about 1.90 percentage points for farming compared to non-farming households. The largest impact is observed for the third time bin. We observe a negative and statistically significant impact of the remaining locust treatment time bins on the probability of being enrolled in school, but the effect becomes smaller over time. This pattern in the estimated regression coefficients holds throughout the different model specifications.[19]

Column (2) presents the estimates of locust exposure on school enrollment with a full set of country-region-year-month fixed effects to flexibly control for unobserved time-varying factors that might affect DHS survey respondents within regions.[20] While the effect of the second time bin becomes statistically insignificant at conventional significance levels, the regression coefficients associated with the treatment interaction terms for time lags $a \geq 3$ remain of the expected negative sign and statistically significant at conventional significance levels. This observation holds throughout the remaining model specifications.

In the following, we examine the sensitivity of the baseline findings to the inclusion of additional geo-spatial controls. In column (3), we include variables for the absolute latitude and longitude of the survey location to account for geographical patterns of locust emergence due, for example, to climatic conditions. Furthermore, the DHS location within the country itself could affect the likelihood of being in school, with DHS locations near coastlines or larger rivers, or further from the country's border, offering more opportunities for schooling. In a similar vein, we include the distance to Christian missions to proxy for the presence of educational facilities in the area.[21] Moreover, the proximity to a town or larger settlement proxies for the availability of educational facilities, whereas distance to the railroad or road network captures the effect of basic transport infrastructure on the probability of attending school.

The estimates presented in column (4) include variables for land quality and elevation to proxy for land suitability for farming on the one hand but also for the flight patterns of desert locusts due to terrain ruggedness on the other hand.

In column (5), we control for the socioeconomic conditions around the DHS survey location. First, we use average nighttime light intensity as a proxy for economic development. Second, we control for total population counts. We hypothesize that the provision of public goods in general and the availability of publicly provided education in particular are higher in areas with a larger population size. Thus, differences in school attendance rates across DHS locations could be partly explained by differences in population size. We further include the incidence of conflict in the regression equation to rule out the possibility that our locust event variable might be correlated with local conflict outbreaks. Conflicts could arise as a consequence of crop failure and be the actual reason for a decline in school attendance.

Finally, column (6) includes climate variables to control for the confounding effect of weather conditions that are either beneficial for locust breeding (e.g., temperature and precipitation) or detrimental to crop farming

[19]In addition, we show the robustness of the main results to a different specification of time bins. Figure D1 in the supplemental material to this paper visualizes alternative bins of 12 months in length, with a lag length of up to 240 months.

[20]Note that this type of fixed effects specification also accounts for unobserved country-specific differences in the overall amount of schooling due, for example, to institutional, economic, and cultural factors.

[21]For example, Jedwab et al. (2021) found that the location of Christian missions is closely related to the dispersion of schools within countries.

(e.g., potential evapotranspiration, number of frost days, and severe drought episodes). Including these variables moderately reduces the magnitude of the effect associated with locust occurrences on farming households. The latter observation provides some evidence that the emergence of locust shocks and climatic conditions are correlated to some extent, and that not controlling for the latter effect would result in partly biased effects of locust events on individual school status.

Overall, we do not observe a significant change in the main findings upon the inclusion of additional covariates, indicating that the former do not capture the effect of the latter on schooling outcomes. This observation provides evidence that the relationship between locust shocks and individual school outcomes is not confounded by observed bio-geographic, socioeconomic, or unobserved time-varying factors around DHS survey locations.

DHS individual and household controls. In the following, we examine the relationship between months of locust infestations and individual school dropout to the inclusion of DHS individual and household-level controls. For example, it is conceivable that household farming status is correlated with household demographic variables (e.g., educational status of the household head). In addition, individual characteristics (e.g., gender or relationship to household head) might explain differences in individual schooling outcomes even within the same household. Thus, Table 3 examines the sensitivity of the main findings to the confounding effects of individual and household-level characteristics. The estimates in column (1) corresponds to those in column (6) of Table 2 with the full set of geographic, distance-based, socioeconomic, conflict, and climate variables and are shown for comparison purposes.

Column (2) shows the results with a parsimonious set of individual characteristics such as gender, relationship to household head (son or daughter), and a full set of age (3-24 years) fixed effects. Regarding the latter controls, we account for age-specific differences in individual schooling outcomes.[22] Locust exposure continues to have a negative and statistically significant effect on school enrollment for farming households, with a considerable increase in the size of the estimated regression coefficients. Children exposed to a single monthly locust event observed 50 km around a DHS location and during the third time bin period prior to the DHS survey date would, ceteris paribus, experience an increase in school dropout of about 4.97 percentage points. This result is quite sizable as it corresponds to a 9.68% change in the mean of the dependent variable ($-4.97/51.34 \approx -0.0968$).

In column (3), we additionally control for DHS household demographic controls (e.g., household size, gender, and level of education of household head). Reassuringly, the baseline results remain qualitatively unchanged to this augmented model specification.

Next, we use a set of household building type, transportation mode, wealth status, and media controls to proxy for the household's wealth condition that might help to mitigate the extent of locust exposure. The corresponding estimates are shown in columns (4)-(7). For example, in column (4), we account for the household's

[22] Likewise, a child's labor productivity in the household increases with age since older children are more likely to perform better on farms than younger ones.

Table 3: Locust Infestations and Individual Schooling Outcomes – Baseline Results with DHS Controls, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Indicator of Currently Being in School							
$TM^{\overline{50}km}_{idct[f(1-24)]} \times Farmer_{hd}$	0.1663	-0.5311	0.0183	0.6152	0.6799	0.5657	0.6615	1.2313*
	(0.8546)	(0.7733)	(0.7246)	(0.6910)	(0.6915)	(0.6812)	(0.6800)	(0.6803)
$TM^{\overline{50}km}_{idct[f(25-48)]} \times Farmer_{hd}$	-0.5463	-0.6370	-0.8535	-1.3137**	-1.2944**	-1.3601***	-1.3725***	-2.6984***
	(0.6689)	(0.5705)	(0.5436)	(0.5357)	(0.5356)	(0.5267)	(0.5269)	(0.4921)
$TM^{\overline{50}km}_{idct[f(49-72)]} \times Farmer_{hd}$	-2.3877**	-4.9700***	-3.7184***	-3.0701***	-2.9822***	-3.1242***	-3.0585***	-1.3201*
	(1.1216)	(0.9960)	(0.9261)	(0.8784)	(0.8758)	(0.8712)	(0.8717)	(0.7892)
$TM^{\overline{50}km}_{idct[f(73-96)]} \times Farmer_{hd}$	-1.8101***	-1.9451***	-1.7743***	-1.6835***	-1.6605***	-1.6270***	-1.6185***	-1.4392***
	(0.4314)	(0.4297)	(0.4021)	(0.3811)	(0.3800)	(0.3768)	(0.3768)	(0.3247)
$TM^{\overline{50}km}_{idct[f(97-120)]} \times Farmer_{hd}$	-0.7906***	-1.6003***	-1.6850***	-1.7711***	-1.7438***	-1.5737***	-1.5673***	-1.5317***
	(0.2903)	(0.2723)	(0.2627)	(0.2498)	(0.2484)	(0.2462)	(0.2461)	(0.2303)
Observations	2,217,852	2,217,852	2,217,852	2,217,852	2,217,852	2,217,852	2,217,852	2,217,846
Adjusted R^2	0.094	0.399	0.412	0.417	0.418	0.420	0.420	0.453
Number of DHS Survey Locations	33498	33498	33498	33498	33498	33498	33498	33492
Mean of Dep. Var.	51.34	51.34	51.34	51.34	51.34	51.34	51.34	51.34
Country×Region×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Land Productivity Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	N/A
DHS Individual Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Household Controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DHS Building Controls	No	No	No	Yes	Yes	Yes	Yes	Yes
DHS Transportation Controls	No	No	No	No	Yes	Yes	Yes	Yes
DHS Wealth Controls	No	No	No	No	No	Yes	Yes	Yes
DHS Media Controls	No	No	No	No	No	No	Yes	Yes
DHS Survey Location FE	No	No	No	No	No	No	No	Yes

Notes: Data are from various DHS survey years in Africa. Observations are at the survey respondent level complemented with household, DHS survey location, and aggregated geo-spatial controls. The dependent variable is a binary indicator of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 3 and 24 years. $TM^{\overline{50}km}_{idct(a)} \times Farmer_{hd}$ is an age-specific locust treatment indicator that counts the number of months of locust infestations during time bin $a \in \mathbb{B} = \{1,2,3,4,5\}$ prior to the DHS survey interview date interacted with the household's farming status. All regressions control separately for household farming status and the various locust treatment bins. *Geographic Controls* include DHS survey location absolute centroid latitude, absolute centroid longitude, distance to the country's border, coastal river, capital city, largest settlement, Catholic missions, Protestant missions, railroads, and roads. *Land Productivity Controls* include mean land suitability for agriculture, mean cropland coverage, mean pasture land, mean elevation, and standard deviation of elevation. *Socioeconomic Controls* include log mean light intensity, log mean population size, and number of conflict events 1-12 months prior to the DHS survey interview date. *Weather Controls* include mean temperature, mean precipitation, mean potential evapotranspiration, drought intensity, and number of frost days 1-12 months prior to the DHS survey interview date. *DHS Individual Controls* include gender of household member ($1 = male$, $0 = female$), indicator variable equal to 1 if the household member is the son or daughter of the household head, and age fixed effects for each age category 3-24 of the household member. *DHS Household Controls* include the gender of the household head ($1 = male$, $0 = female$), indicator variables for each household size category ($1-9$ and > 10 household members), and indicator variables for the household head's highest attained educational level (i.e., primary, secondary, and higher education). *DHS Building Controls* include indicator variables of whether the household has access to electricity, pipe water, and finished floor construction. *DHS Transportation Controls* include indicator variables of whether the household has a car or truck, a motorcycle or scooter, or a bike. *DHS Wealth Controls* include indicator variables of the household's wealth status (i.e., poor or middle wealth groups). *DHS Media Controls* include indicator variables of whether the household has a radio or television. $Country \times Region \times Time\ FE$ are fixed effects of the calendar year and month of the country's region according to the DHS data. See the main text for additional details on data construction and sources. Clustered standard errors by DHS survey location level are shown in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

access to electricity, pipe water, whether the main flooring material is finished (relative to rudimentary and natural), and whether the household has a toilet facility available. We see a quite significant effect on the estimated regression coefficient associated with the second locust treatment bin variable. The results show that a single monthly locust event experienced 3-4 years prior to the DHS survey date would, ceteris paribus, increase individual school dropout by about 1.31 percentage points. Overall, the estimates related to the remaining locust treatment variables remain of the expected negative sign and statistically significant at conventional significance levels when we control for additional DHS household controls, as evidenced in columns (5)-(7).

Finally, in column (8), we estimate the main regression equation with an exhaustive set of DHS survey location fixed effects. In this model specification, we are able to control for unobserved local DHS survey location characteristics that might be correlated with both our locust treatment control and overall school enrollment status. As a consequence, the set of geographic, land productivity, socioeconomic, and weather controls drop out of the regression model due to perfect collinearity with DHS survey location fixed effects. This model specification only exploits variation across survey respondents within the same DHS survey location who were affected differently by locust shocks due to the age of school-aged survey respondents. For the first time bin, there is a positive but statistically weak relationship to school enrollment status, which might be consistent with the idea that school enrollment increases in the short run due to devastated crop yields resulting from unexpected locust events. More importantly, the main findings regarding the detrimental impact of locust exposure on individual school status for farming households remain qualitatively unaltered even in this augmented model specification. Since the inclusion of DHS survey location fixed effects absorbs much of the identifying variation in our estimations and because overall model fit does not increase substantially, we focus our attention on the robustness of the findings in column (7) of Table 3.

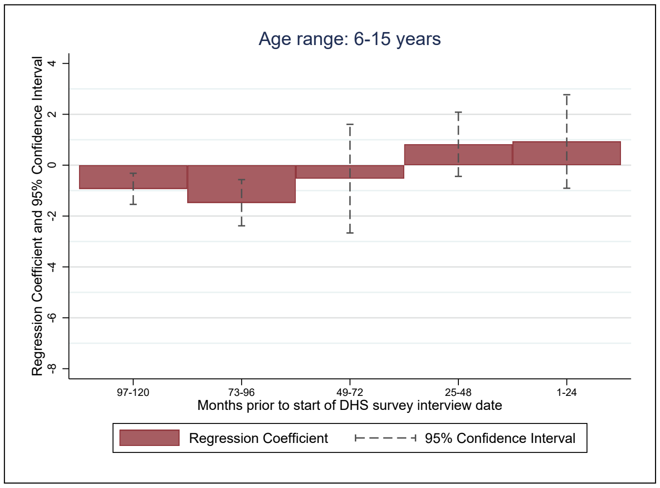
It is worth noting that the results presented in Table 2 and 3 are also robust to specifications based on years of schooling as an alternative dependent variable. The intent of this is to capture the long-run impact on accumulated years of schooling as a stock measure rather than enrollment status as a current investment or flow variable. [23]

Age- and gender-specific effects of locust infestations. Household composition is critical in determining an individual's participation in school and household activities. The number of people living in the household, the gender, and the number of adult children may determine how a person's time is split between household production and school. We examine the possibility that, depending on the family composition, locust-affected households cope with infestations by having children in the household participate in farm work. Since our data do not provide information on child labor, we examine this hypothesis to determine whether older children in locust-affected households are more likely to drop out of school. We further complement our analyses with an examination of gender-based treatment at home.

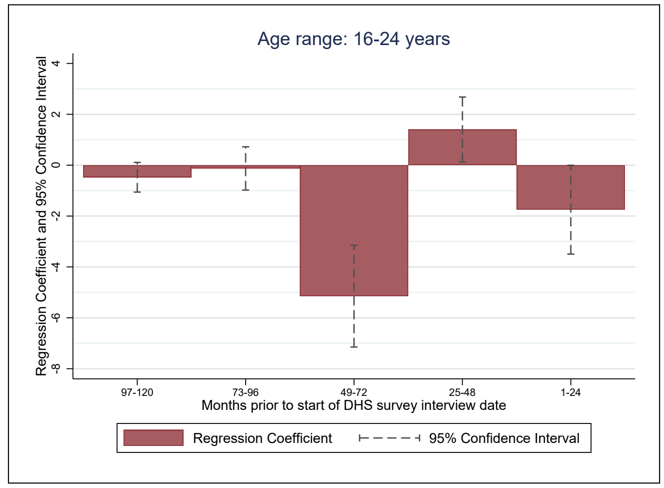
The upper part of Figure 3 shows heterogeneous effects of locust infestations for individuals between the ages of 6 and 15 and 16 and 24. The graph suggests that the impact of locust shocks on the likelihood of attending school depends on the timing of the shocks and varies across age groups. First, Panel (a) shows that children between the ages of 6 and 15 are not affected by recent locust events but rather by events in the past, which occurred between 73 to 120 months prior to the survey date. A possible explanation for this pattern could be that young children's school enrollment is delayed to cope with the adverse effects of long-run infestations.

Panel (b) shows a diverse pattern, where individuals aged 16 to 24 are less likely to attend school for the first two years, possibly due to their higher relative productivity and effectiveness in farm work (Beegle et al., 2003). However, this is followed by an increase in the probability of attending school in months 25 to 48

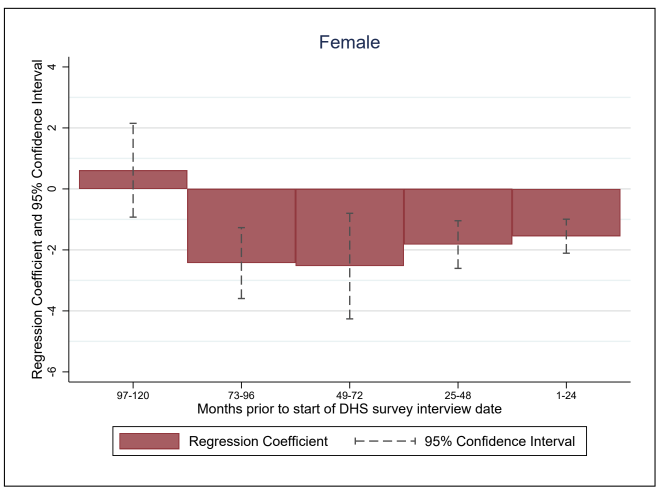
[23] A summary of these results is provided in Figure D2 and in Table C3 in the supplemental material to this paper.



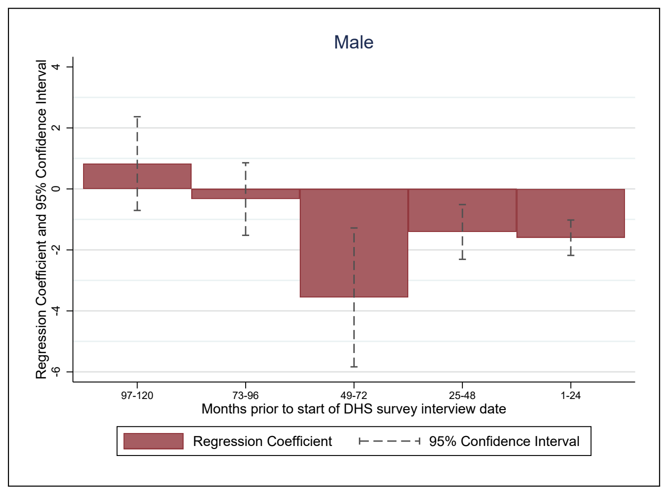
(a) Age range: 6-15 years



(b) Age range: 16-24 years



(c) Gender: female



(d) Gender: male

Figure 3: Age- and Gender-Specific Effects of Locust Exposure on School Enrollment

Notes: The figure presents estimated regression coefficients β_3^a and the corresponding 95% confidence interval from estimations of regression equation (4) for different age- and gender-specific samples on the various time lag bins $a \in \mathbb{B} = \{1,2,3,4,5\}$ of the locust treatment control $TM^{\bar{b}km}_{idct(a)}$ interacted with the household farming status variable $Farmer_{hd}$. The outcome variable is an indicator variable of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 6 and 24, Panels (a) and (b), and 3 and 24, Panels (d) and (c). The regression includes a full set of controls according to model specification (7) in Table 3. See the main text for additional details on data construction, sources, and estimation methodology.

and, subsequently, by a significant drop in months 49 to 72. Locust infestations that date back 73 months or more have no significant impact on the probability of enrollment in this age group. A possible explanation for this pattern could be that after the initial repercussions of the income shock, children are no longer needed for additional farm work and can be sent back to school (Zimmermann, 2020).

Overall, the results suggest that older children are pulled out of school immediately in response to a negative shock, in line with the child labor substitution hypothesis (Cockburn and Dostie, 2007). Furthermore, the need for young children to help with farm work appears to be lower during more recent locust outbreaks, meaning that younger children are less negatively affected by transitory infestations and more negatively affected by persistent infestations.

The bottom part of Figure 3 presents heterogeneous results on the propensity to attend school by gender for all ages, that is, 3 to 24 years. The key assumption underlying this model specification is that locust outbreaks have a more severe negative impact on the likelihood to attend school for females (see Panel (c)) relative to males (see Panel (d)).[24] Within the same gender group, girls and young women in farming households are more negatively affected by locust outbreaks than their peers in non-farming households. Panel (d) suggests that males are more insulated from the long-run impact (73 to 120 months) of locust infestations than females, for whom Panel (c) shows an adverse effect persisting to up to 96 months after the locust infestation.[25]

Taken together, the results in Figure 3 show a differential effect of locust outbreaks on schooling by gender and age of survey respondents, confirming possible discrimination in farming households in the event of natural shocks. The estimates are consistent with child labor substitution and the opportunity cost model, illustrating that locust-affected households tend to substitute older household members for home production to compensate for unexpected losses in income, leading to lower school enrollment (Beegle et al., 2003). Overall, we can deduce that school dropout and participation in household labor rise with age in locust-affected households.

Heterogeneous effects: Educational level of household head. The educational level of the parent or household head is a crucial factor affecting investments in children's education. It also serves as a proxy for household wealth, given that educated household heads are observed to be more affluent than their non-educated counterparts (Dung, 2013). Furthermore, the value educated parents place on education could impact their reaction to income shocks, such that higher-educated household heads are more willing to continue allocating resources to education during shocks. Accordingly, the educational level of the household head buffers against the adverse effect of locust outbreaks, as it captures the value the household places on education.

Thus, Table 4 presents heterogeneous estimates of locust events on schooling outcomes by the household head's educational status, where the results in columns (1)-(4) show estimates for schooling status. The mean of the dependent variable increases as we go from columns (1)-(4). This finding suggests that the household head's educational status is significantly correlated with the child's schooling outcomes.[26]

Overall, the estimates show quite significantly that the likelihood of school dropout among school-aged children decreases with the household head's educational status. It is worth noting that no matter what the household head's educational level, locust events have a long-run effect on school enrollment status. Nevertheless, the effect may be less robust for highly educated household heads.

[24]This might be due greater responsibility women traditionally hold for domestic labor (Dillon, 2012).

[25]The evidence suggests that short-term response to a locust outbreak accounts for permanent adverse effects on girls' educational outcomes (Zamand and Hyder, 2016; Dung, 2013; Krutikova, 2010).

[26]In addition, we repeat this analysis with years of schooling as the dependent variable to highlight the long-term impact of locust outbreaks on educational stocks. See Table C1 in the supplemental material to this paper.

Table 4: Locust Infestations and Individual Schooling Outcomes – Heterogeneous Effects by Educational Level of Household Head

	(1)	(2)	(3)	(4)
	Educational Level of Household Head			
	No Schooling	Primary	Secondary	Higher
	Indicator of Currently Being in School			
$TM^{\overline{50km}}_{idct[f(1-24)]} \times Farmer_{hd}$	1.0222	-0.7229	-1.0045	-1.4672
	(0.8728)	(0.8861)	(1.6730)	(2.2016)
$TM^{\overline{50km}}_{idct[f(25-48)]} \times Farmer_{hd}$	0.3021	-1.7037**	-0.6776	1.5740
	(0.7446)	(0.7655)	(0.7469)	(1.1652)
$TM^{\overline{50km}}_{idct[f(49-72)]} \times Farmer_{hd}$	-2.6027**	1.6584	-2.9225	0.5505
	(1.2062)	(1.1479)	(2.1797)	(2.3478)
$TM^{\overline{50km}}_{idct[f(73-96)]} \times Farmer_{hd}$	-0.6783	-0.8473	-1.7381**	-1.1158
	(0.4362)	(0.6180)	(0.7483)	(1.3657)
$TM^{\overline{50km}}_{idct[f(97-120)]} \times Farmer_{hd}$	-0.7610***	-1.2262**	-1.1421**	-1.5146
	(0.2857)	(0.5177)	(0.5788)	(1.2164)
Observations	910,049	738,445	444,316	124,888
Adjusted R^2	0.339	0.470	0.480	0.421
Number of DHS Survey Locations	29470	30957	28030	14971
Mean of Dep. Var.	40.25	56.33	60.89	68.75
Country×Region×Time FE	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes
Land Productivity Controls	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
DHS Individual Controls	Yes	Yes	Yes	Yes
DHS Household Controls	Yes	Yes	Yes	Yes
DHS Building Controls	Yes	Yes	Yes	Yes
DHS Transportation Controls	Yes	Yes	Yes	Yes
DHS Wealth Controls	Yes	Yes	Yes	Yes
DHS Media Controls	Yes	Yes	Yes	Yes

Notes: This table shows regressions from estimating Equation (4) for different samples according to the educational level of the household head (i.e., no schooling, primary, secondary, and higher education). Data are from various DHS survey years in Africa. Observations are at the survey respondent level, complemented with household, DHS survey location, and aggregated geo-spatial controls. The dependent variable is a binary indicator of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 3 and 24 years. $TM^{\overline{50km}}_{idct(a)} \times Farmer_{hd}$ is an age-specific locust treatment indicator that counts the number of months of locust infestations during time bin $a \in \mathbb{B} = \{1,2,3,4,5\}$ prior to the DHS survey interview date, interacted with the household's farming status. All regressions control separately for household farming status and the various locust treatment bins. *Geographic Controls* include DHS survey location absolute centroid latitude, absolute centroid longitude, distance to the country's border, coastal river, capital city, largest settlement, Catholic missions, Protestant missions, railroads, and roads. *Land Productivity Controls* include mean land suitability for agriculture, mean cropland coverage, mean pasture land, mean elevation, and standard deviation of elevation. *Socioeconomic Controls* include log mean light intensity, log mean population size, and number of conflict events 1-12 months prior to the DHS survey interview date. *Weather Controls* include mean temperature, mean precipitation, mean potential evapotranspiration, drought intensity, and number of frost days 1-12 months prior to the DHS survey interview date. *DHS Individual Controls* include gender of household member ($1 = male$, $0 = female$), indicator variable equal to 1 if the household member is the son or daughter of the household head, and age fixed effects for each age category 3-24 of the household member. *DHS Household Controls* include the gender of the household head ($1 = male$, $0 = female$), indicator variables for each household size category ($1-9$ and > 10 household members), and indicator variables for the household head's highest attained educational level (i.e., primary, secondary, and higher education). *DHS Building Controls* include indicator variables of whether the household has access to electricity, pipe water, and finished floor construction. *DHS Transportation Controls* include indicator variables of whether the household has a car or truck, a motorcycle or scooter, or a bike. *DHS Wealth Controls* include indicator variables of the household's wealth status (i.e., poor or middle wealth groups). *DHS Media Controls* include indicator variables of whether the household has a radio or television. $Country \times Region \times Time\ FE$ are fixed effects of the calendar year and month of the country's region according to the DHS data. See the main text for additional details on data construction and sources. Clustered standard errors by DHS survey location level are shown in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

5.2 Sensitivity Analysis

Robustness to different buffer sizes. In Figure 4, we estimate the baseline specification for different buffer sizes (i.e., 20, 30, and 40 km) across the different locust treatment time bins. In Panel (a), we plot the regression coefficients and the corresponding 95% confidence interval of the locust treatment control interacted with the household farming status variable from our baseline model specification (see column (7) of Table 3).

Importantly, we find that there is no qualitative difference in the likelihood of school dropout after locust outbreaks across the different buffer sizes. Specifically, locust infestations within two years have no significant impact on school enrollment status across all buffer sizes. Second, events that are between two and ten years have a significant effect on locust-affected farming households (except for 3 to 4 years of the 20 km buffer specification). Estimates of locust impact on schooling for farming households remain unchanged and follow the same pattern for buffer sizes 20 km and above.

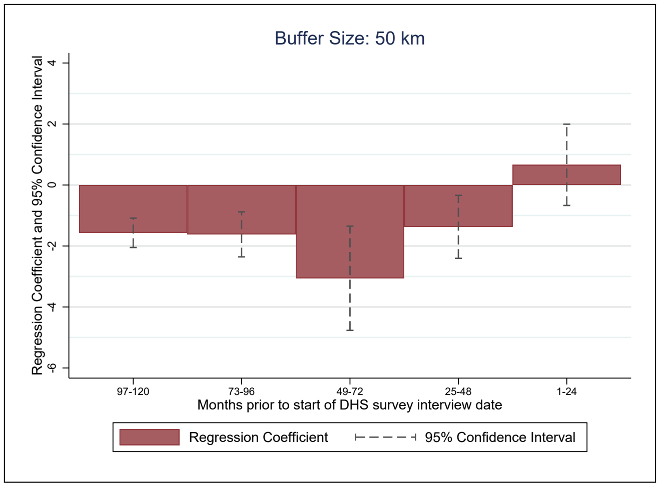
Robustness to different model specifications and samples. Next, we subject our baseline results to different model specifications. We run separate regressions for swarms and bands (bands are wingless adults, giving us a more localized impact of outbreaks). In addition, we restrict our sample to locust-infested countries only and subject the regressions to different sample sizes according to the number of individuals within DHS survey locations. We present the estimates in Table 5. We report the baseline results in column (1) for comparison purposes.

The estimates in columns (2) and (3) focus on different types of locust outbreaks, while column (4) reports the estimates when including only locust-infested countries in the empirical analysis. Columns (5)-(10) are the results when we restrict our sample by the number of individuals within a DHS survey location.

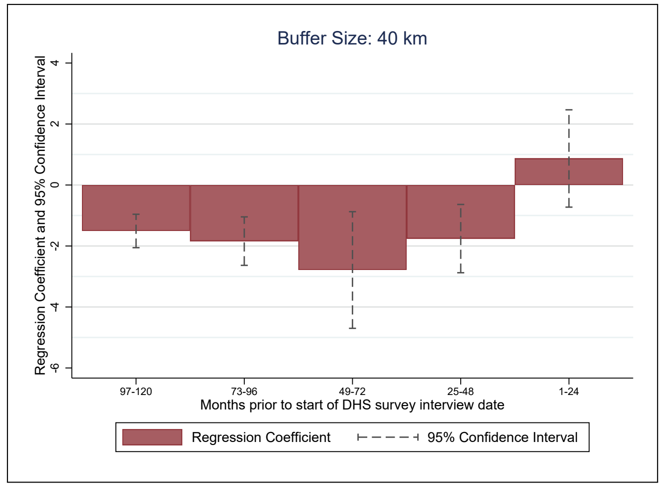
The estimates once again showcase that, irrespective of the model specification, infestations experienced in the first or second year prior to the DHS survey date do not significantly affect the school enrollment status of locust-affected farming households. However, later locust treatment time bins show a significant and adverse effect on the individual propensity to attend school. For example, the estimates shown in column (2) suggest that locust band outbreaks have a more pronounced effect on schooling outcomes than locust swarms. One could argue that locust band infestations are more localized and might have more volatile effects on farming households' incomes. Additionally, our identification allows us to restrict the sample to locust-infected countries only, as reported in column (4). Reassuringly, the main results remain largely unchanged.[27]

Finally, we redefine the regression sample to include a minimum number of individuals across DHS survey locations (i.e., 5, 10, 20, 30, 40, and 50 individuals). The corresponding estimates based on the stepwise elimination of the respective survey locations are shown in columns (6)-(10). Reassuringly, we can reject concerns that our main findings might be sensitive to differences in the minimum number of sampled individuals across DHS survey locations.

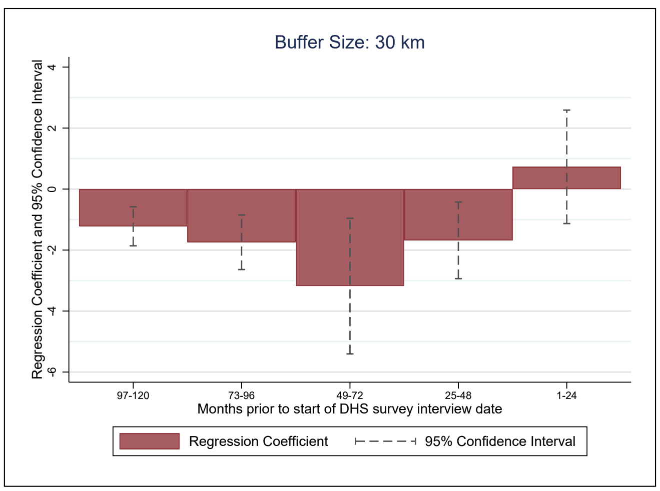
[27] Similarly, the results remain unchanged to subsequently leaving one country out of the regression sample, as shown in Figure D3 in the supplemental material to this paper.



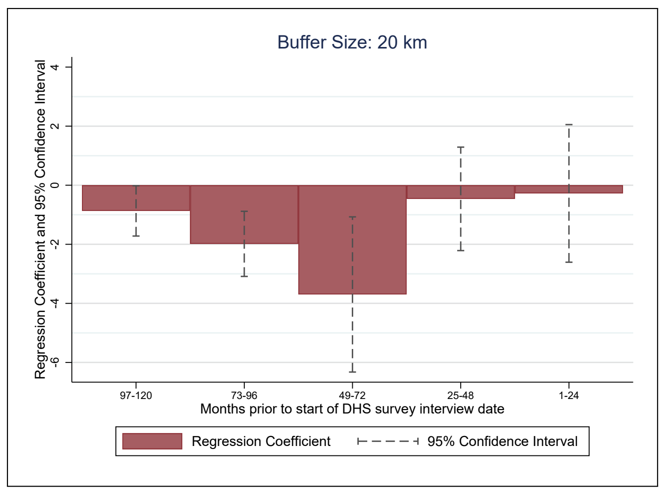
(a) Buffer Size: 50 km



(b) Buffer Size: 40 km



(c) Buffer Size: 30 km



(d) Buffer Size: 20 km

Figure 4: Robustness to Different Buffer Sizes Around DHS Survey Location

Notes: The figure presents estimated regression coefficients β_3^a and the corresponding 95% confidence interval from estimating regression equation (4) for different buffer sizes $\bar{b} = \{50, 40, 30, 20\}$ (in km) on the different time lag bins $a \in \mathbb{B} = \{1, 2, 3, 4, 5\}$ of the locust treatment control $TM_{idct(a)}^{\bar{b}km}$ interacted with the household farming status variable $Farmer_{hd}$. The outcome variable is an indicator variable of currently being in school (100 = *yes*, 0 = *no*) for individuals between the ages of 3 and 24 years. The regressions include a full set of controls according to model specification (7) in Table 3. See the main text for additional details on data construction, sources, and estimation methodology.

Table 5: Locust Infestations and Individual Schooling Outcomes – Robustness to Different Model Specifications and Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Locust Indicator			Sample	Minimum Number of DHS Survey Location Observations					
	Swarms and Bands	Locust Swarms	Locust Bands	Locust countries	5	10	20	30	40	50
	Indicator of Currently Being in School									
$TM^{\overline{50km}}_{idct[f(1-24)]}\times Farmer_{hd}$	0.6615	0.3360	0.8587	0.8589	0.6597	0.6568	0.5147	0.5851	1.0035	1.5422*
	(0.6800)	(0.7184)	(1.6023)	(0.6733)	(0.6801)	(0.6804)	(0.6874)	(0.6991)	(0.7536)	(0.8329)
$TM^{\overline{50km}}_{idct[f(25-48)]}\times Farmer_{hd}$	-1.3725***	-1.2366**	-2.7710**	-1.0853**	-1.3727***	-1.3580***	-1.2355**	-1.0628*	-1.0144*	-1.1805*
	(0.5269)	(0.5995)	(1.3172)	(0.5249)	(0.5269)	(0.5270)	(0.5341)	(0.5534)	(0.6044)	(0.6900)
$TM^{\overline{50km}}_{idct[f(49-72)]}\times Farmer_{hd}$	-3.0585***	-3.3914***	0.2578	-2.3379***	-3.0578***	-3.0582***	-3.0531***	-2.9894***	-3.0737***	-2.7519***
	(0.8717)	(0.8448)	(5.6369)	(0.8527)	(0.8717)	(0.8716)	(0.8705)	(0.8811)	(0.9202)	(0.9612)
$TM^{\overline{50km}}_{idct[f(73-96)]}\times Farmer_{hd}$	-1.6185***	-1.5868***	-2.6243**	-1.2657***	-1.6180***	-1.6175***	-1.6179***	-1.6200***	-1.5886***	-1.6090***
	(0.3768)	(0.3904)	(1.0366)	(0.3696)	(0.3768)	(0.3768)	(0.3770)	(0.3790)	(0.3851)	(0.3952)
$TM^{\overline{50km}}_{idct[f(97-120)]}\times Farmer_{hd}$	-1.5673***	-1.6568***	-3.1862***	-1.3255***	-1.5683***	-1.5634***	-1.5199***	-1.5661***	-1.6957***	-1.7676***
	(0.2461)	(0.2614)	(0.6643)	(0.2434)	(0.2461)	(0.2467)	(0.2496)	(0.2558)	(0.2640)	(0.2710)
Observations	2,217,852	2,217,852	2,217,852	1,343,852	2,217,695	2,216,281	2,202,982	2,157,442	2,058,708	1,877,487
Adjusted R^2	0.420	0.420	0.420	0.407	0.420	0.420	0.419	0.418	0.415	0.413
Number of DHS Survey Locations	33498	33498	33498	19548	33445	33251	32377	30564	27727	23674
Mean of Dep. Var.	51.344	51.344	51.344	47.883	51.344	51.345	51.333	51.237	50.957	50.413
Country×Region×Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Land Productivity Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Household Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Building Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Transportation Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Wealth Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DHS Media Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Data are from various DHS survey years in Africa. Observations are at the survey respondent level complemented with household, DHS survey location, and aggregated geo-spatial controls. The dependent variable is a binary indicator of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 3 and 24 years. $TM^{\overline{50km}}_{idct(a)}\times Farmer_{hd}$ is an age-specific locust treatment indicator that counts the number of locust infested months during time bin $a \in \mathbb{B} = \{1,2,3,4,5\}$ prior to the DHS survey interview date interacted with the household's farming status. All regressions separately control for household farming status and the various locust treatment bins. *Geographic Controls* include DHS survey location absolute centroid latitude, absolute centroid longitude, distance to the country's border, coastal river, capital city, largest settlement, Catholic missions, Protestant missions, railroads, and roads. *Land Productivity Controls* include mean land suitability for agriculture, mean cropland coverage, mean pasture land, mean elevation, and standard deviation of elevation. *Socioeconomic Controls* include log mean light intensity, log mean population size, and number of conflict events 1-12 months prior to the DHS survey interview date. *Weather Controls* include mean temperature, mean precipitation, mean potential evapotranspiration, drought intensity, and number of frost days 1-12 months prior to the DHS survey interview date. *DHS Individual Controls* include gender of household member ($1 = male$, $0 = female$), indicator variable equal to 1 if the household member is the son or daughter of the household head, and age fixed effects for each age category 3-24 of the household member. *DHS Household Controls* include the gender of the household head ($1 = male$, $0 = female$), indicator variables for each household size category ($1-9$ and > 10 household members), and indicator variables for the household head's highest attained educational level (i.e., primary, secondary, and higher education). *DHS Building Controls* include indicator variables of whether the household has access to electricity, pipe water, and finished floor construction. *DHS Transportation Controls* include indicator variables of whether the household has a car or truck, a motorcycle or scooter, or a bike. *DHS Wealth Controls* include indicator variables of the household's wealth status (i.e., poor or middle wealth groups). *DHS Media Controls* include indicator variables of whether the household has a radio or television. $Country \times Region \times Time\ FE$ are fixed effects of the calendar year and month of the country's region according to the DHS data. See the main text for additional details on data construction and sources. Clustered standard errors by DHS survey location level are shown in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

5.3 Mechanisms

One plausible mechanism that explains the reduction in schooling is that relatively poorer households may disproportionately allocate more time to work on the farm in response to locust outbreaks. This forces children to take time from attending school to working on the fields. In contrast, affluent households who can cope with income losses caused by the outbreak may be more concerned with keeping their wards in school rather than preserving household food security and income.

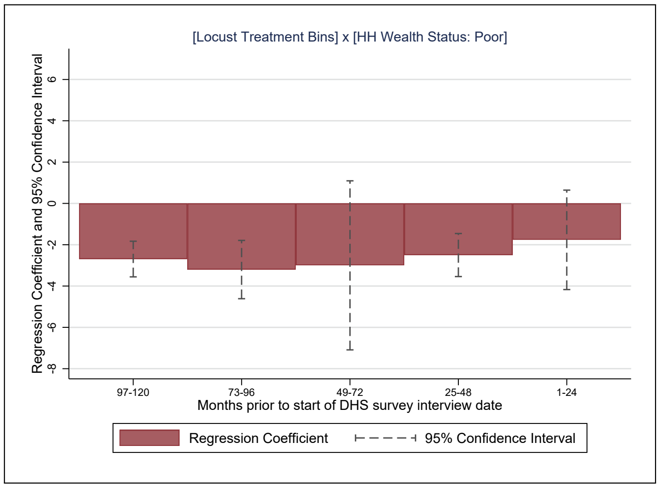
However, in most African communities, this situation only applies to a small number of wealthy households. Even though primary education is free in certain African nations, parents contribute more than the government allots to schools (Goromonzi, 2023). Households face many difficulties when school funding is delayed, and shocks further endanger their earnings. Sometimes income shocks caused by unexpected high inflation rates render the average family (including teachers) unable to send children to school because real income earned is less than their monthly expenditure (Goromonzi, 2023).

To elaborate further on our results, we take an exploratory approach to the mechanisms that mediate exposure to locust infestations in individual school dropouts. A more comprehensive analysis of this critical issue requires detailed information on household consumption patterns for child schooling and changes in household income caused by locust events. This kind of analysis would require more exhaustive data on households observed over time and is beyond the scope of the current research. However, we rely on wealth status and land size household information in our data. We analyze household wealth status by examining how education affects poor, middle-income, and wealthier locust-affected households, distinguishing between all affected and farming households.

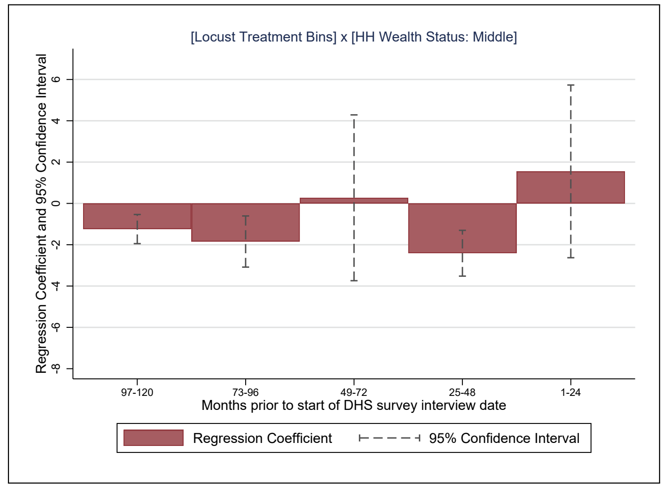
The estimates for households considered as belonging to the poor or middle wealth groups of the general population are shown in Panels (a) and (b), respectively, of Figure 5. Panels (c) and (d) show the results for poor and middle-income farming households. The estimates in Panel (a) suggest that locust shocks have more negative long-term effects on school attendance in poorer households than in wealthier households. However, Panel (c) shows that being a poor farmer does not significantly affect the propensity to stay in school since children from poor farming households generally have a lower tendency to be in school than those from affluent farming households. The estimates depicted in Panels (b) and (d) reveal that households with a middle wealth status have a higher tendency to adjust children's school attendance than households with a high wealth status.

To elaborate more on our income shock hypotheses, Figure 6 presents the results by farm size. We split the household farming status into small farms with less than 2 hectares of farmland, medium farms with 2 to 5 hectares of farmland, and large farms with more than 5 hectares of farmland (World Bank, 2003). We expect that depending on the size of the farm, the impact of locust infestations on schooling decisions will vary. The result aligns with our main hypothesis that destruction of crops and pastureland by desert locusts could lead to catastrophic losses of yields and income. The effect may even be more pronounced for farmers with large-sized farms.[28] If expected returns from crop yield fall due to infestations, there will be a higher tendency for children

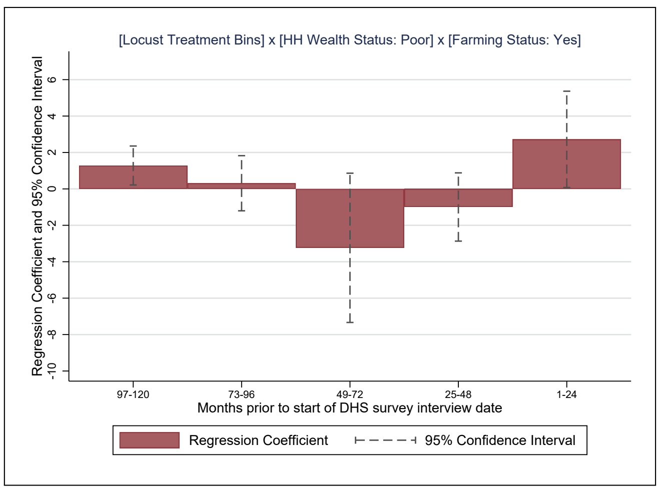
[28] According to Bola (2020), the desert locust has an exceptional ability to consume a wide variety of foods and thus to damage



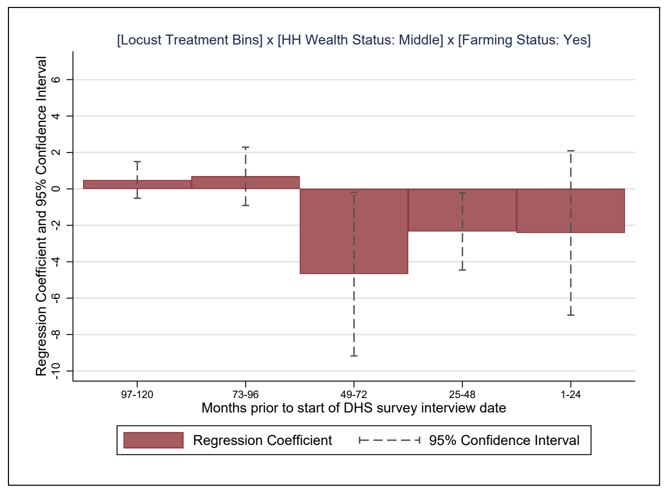
(a) $TM^{\overline{50km}}_{idct(a)} \times [Wealth:\ Poor]$



(b) $TM^{\overline{50km}}_{idct(a)} \times [Wealth:\ Middle]$



(c) $TM^{\overline{50km}}_{idct(a)} \times [Wealth:\ Poor] \times [Farming:\ Yes]$



(d) $TM^{\overline{50km}}_{idct(a)} \times [Wealth:\ Middle] \times [Farming:\ Yes]$

Figure 5: Mechanisms: Household Wealth Status

Notes: The figure shows heterogeneous locust effects on school enrollment status by household wealth status. Panel (a) and (b) report coefficient estimates and the corresponding 95% confidence interval of the locust treatment control $TM^{\overline{bkm}}_{idct(a)}$ interacted with the household wealth status = $\{poor, middle, rich\}$. Panel (c) and (d) show heterogeneous effects of locust infestations on school enrollment status by household wealth, but for farming and non-farming households separately. Estimated regression coefficients are relative to the excluded base wealth category *rich*. All regressions separately control for household wealth and farming status and the full set of controls according to model specification (7) in Table 3. The outcome variable is an indicator variable of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 3 and 24 years. See the main text for additional details on data construction, sources, and estimation methodology.

to work on the farm to serve as a cheaper, more convenient way of coping with locust outbreaks.[29]

virtually all types of vegetation and crops. Cereal crops, including wheat, barley, millet, maize, sorghum, and rice, are particularly vulnerable, but even vines, citrus fruits, palm trees, date palms, and vegetable crops may be affected. Grazing areas also undergo significant destruction, affecting total biomass production and its palatability to livestock.

[29] Zamand and Hyder (2016) found that poor children in developing nations are the group at highest risk due to climate shocks.

Although locust infestations could impact schooling status directly, the main impact is an income effect. In our context, loss of income due to crop variability induced by locust shocks could force households to change children's school attendance. Indeed, the magnitude of the effect of locust infestations on education might depend on the household's vulnerability and ability to quickly mobilize labor to work on the farm.

Panel (a) of Figure 6 shows that locusts only have long-term effects (i.e., locust infestations 73 to 120 months prior to the survey date) on farmers with small-sized farms, who may find it challenging to recover from their losses. It is possible that in the case of these small farms of less than 2 hectares of land, locust swarms rapidly devastate crops and lead to acute losses that can have prolonged effects (Zhang et al., 2019). When locust outbreaks become more frequent, small farm owners are likely to develop alternative ways of mitigating the risk of crop loss such as going out of the farming business, confirming the income compensation hypothesis (Agamile et al., 2021). For individuals in households with medium-sized farms, Panel (b) shows a similar pattern, although they are only affected by locust outbreaks dating back more than 97 months.

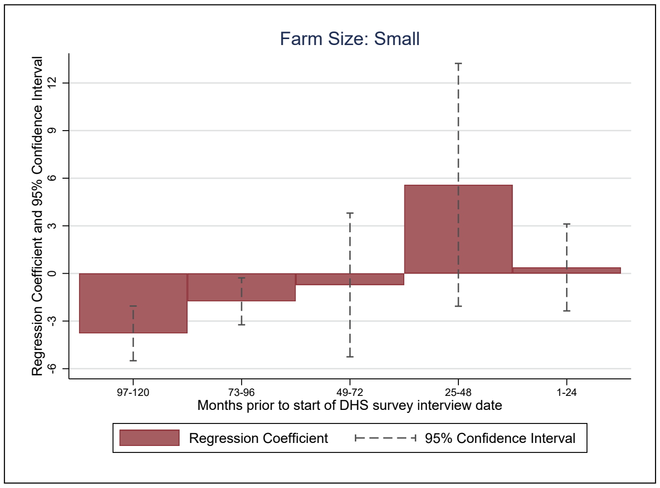
Panel (c) shows the results for owners of large farms. As we expected, owning more farmland leads to greater short- and long-term effects on the probability of school attendance among individuals in farming households than among those in non-farming households. The result is more pronounced for households with large farms because having more hectares of land leads to a greater risk of yield loss and the need for more labor to work on the farm. The implication is that, in contrast to subsistence farming households (with small farms), which lose their main food source due to locust infestations, households with larger amounts of farmland are deprived of their main source of income. In such instances, with limited labor at hand, households with large farms have a higher propensity to pull individuals out of school to help save crops, replant, and avoid spending money to hire additional labor. These households also cannot manage infestations in the long run due to the randomness and consumption rate of the locust outbreaks. Hence, we see a decreasing ability to recover from past infestations over time.

Our findings confirm that once an individual leaves school, it becomes almost impossible for them to return.[30] Our results further emphasize that locust-prone households that rely heavily on agriculture are less resilient to locust plagues due to the limited availability of non-farming jobs (Cease et al., 2015).

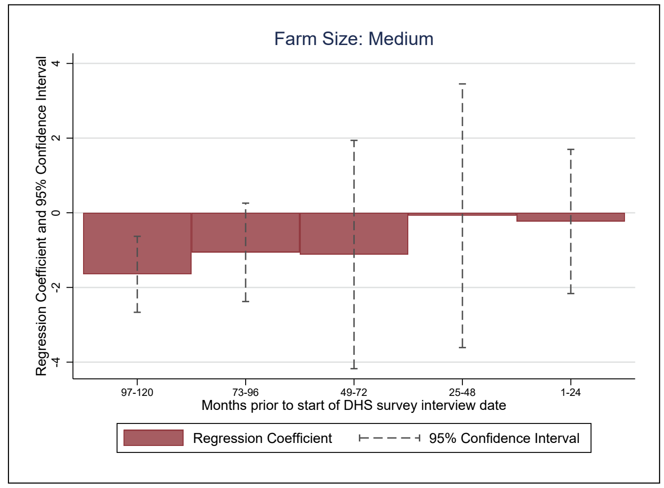
To summarize, household wealth and the ability to cope with locust outbreaks significantly affect an individual's probability of staying in school. The revealed pattern supports of our argument that the effect of locust infestations is highly dependent on the wealth and economic status of the household. Children from relatively poor farming households may be permanently prevented from returning to school due to the sustained effect of locust outbreaks and the inability of these households to smooth consumption in the long run (Mahmud and Riley, 2021; Marchetta et al., 2018). Children from households with large farms may also be permanently

Adverse shocks affecting agricultural output and income can significantly reduce investments in children's nutrition and education. These factors depend on the nature and magnitude of the shock, characteristics of the children, parental preferences, household wealth, and assets that can help to buffer the impact of shocks on the household's credit constraints.

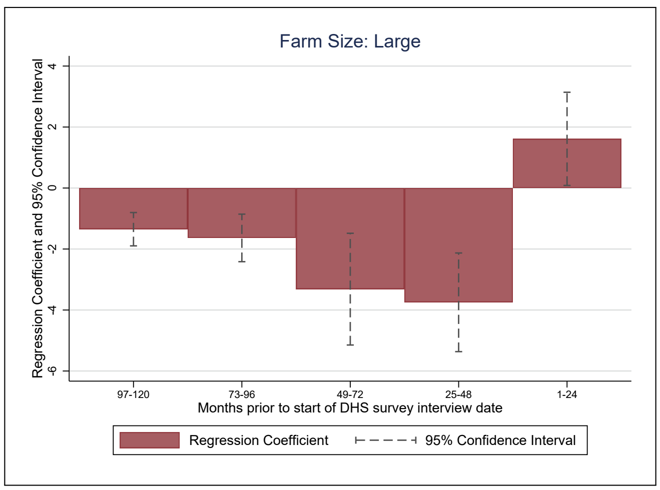
[30]See Kazianga (2012), who found that after a plague, even if it may not necessarily occur again in the future, households have a sufficient reason not to send children back to school because with an unstable income, spending less on education and preserving more money is preferable in case of a shock.



(a) $TM^{\overline{50}km}_{idct(a)} \times [Farm\ Size:\ Small]$



(b) $TM^{\overline{50}km}_{idct(a)} \times [Farm\ Size:\ Medium]$



(c) $TM^{\overline{50}km}_{idct(a)} \times [Farm\ Size:\ Large]$

Figure 6: Mechanisms: Household Farm Size

Notes: The figure presents estimated regression coefficients β_3^a and the corresponding 95% confidence interval from estimating regression equation (4) on the different time lag bins $a \in \mathbb{B} = \{1,2,3,4,5\}$ of the locust treatment control $TM^{\bar{b}km}_{idct(a)}$ interacted with the household $farm\ size = \{small, medium, large\}$. The outcome variable is an indicator variable of currently being in school ($100 = yes$, $0 = no$) for individuals between the ages of 3 and 24 years. The regression includes the full set of controls according to model specification (7) in Table 3. See the main text for additional details on data construction, sources, and estimation methodology.

prevented from returning to school, but in this case due to the inability of these households to recover from the loss of income.

5.4 Estimated Effects on Schooling from Rising Global Temperatures

To establish a link between the evolution of global temperatures and the risk of locust outbreaks, we are interested in the association of temperature anomalies and locust occurrences. Accordingly, Figure 7 provides a stylized representation of how the spatial distribution of locust infestations and temperature anomalies coincide. The data are aggregated to rectangular grids of 0.25 DD size for the sake of clarity. Panel (a) shows the average annual change in yearly average ground temperature between 1985 and 2020, measured in degrees Celsius. Positive anomalies are depicted in yellow (light) and negative anomalies in purple (dark). The most pronounced positive anomalies occurred in coastal regions of West Africa (for example, Mauritania, Senegal, and Gambia), which show average yearly increases of up to 0.04 $^{\circ}C$. Over the 36-year period, this corresponds to a total temperature increase of 1.4 $^{\circ}C$. Coastal regions in Northern Africa (for example, Morocco and Egypt), as well as in Central Africa (e.g., Cameroon and Gabon) experienced similar increases in average temperatures, although at a lower level. Last, the East African countries south of the Horn of Africa have also been affected by a clear rise in average temperatures.

These findings are complemented by Panel (b), which, for the same time period, shows the total number of locust infestations, counting both locust swarms and bands. Grid cells with at least one infestation are shown in dark blue, whereas a higher number of infestations per cell are associated with lighter colors, with 250 and above being the maximum, shown in yellow. Interestingly, the countries and regions that have experienced the highest increases in average temperature are also strongly affected by locust infestations (see, e.g., Senegal, Gambia, Morocco, and Kenya). Overall, locust infestations seem to occur mainly in the coastal regions that face rising temperatures rather than in inland areas.

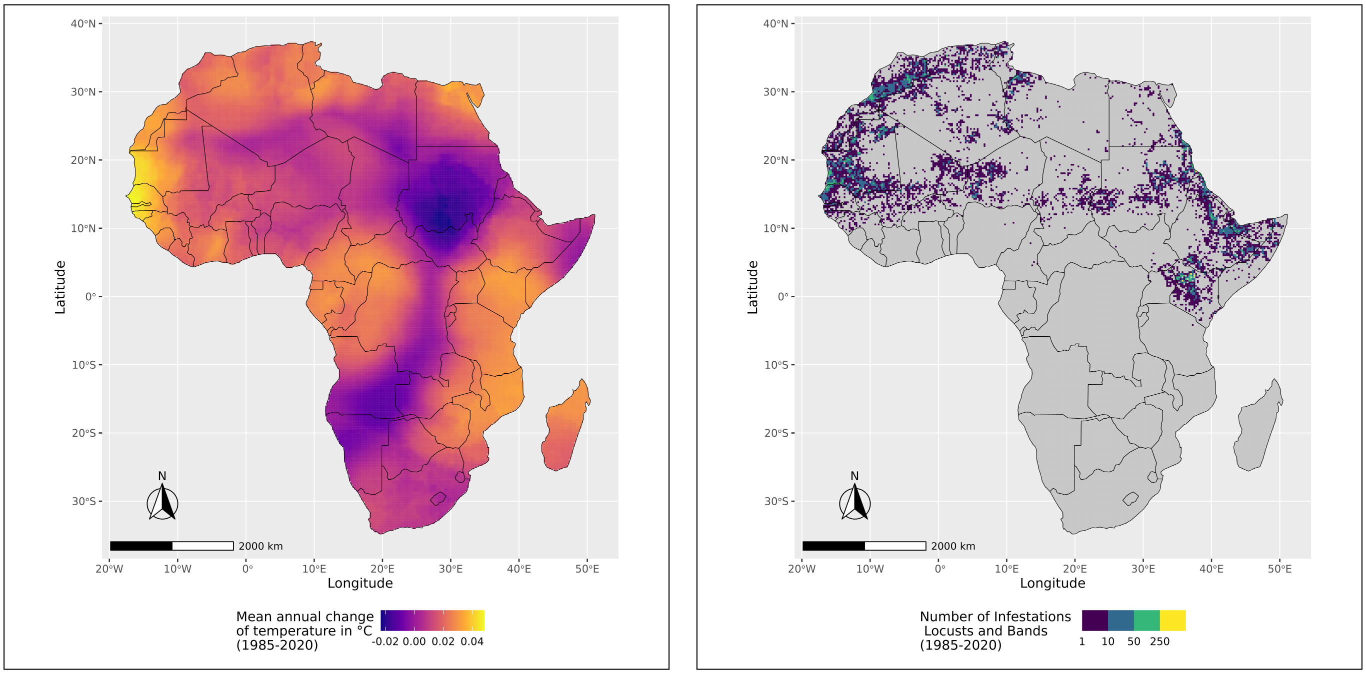
In the face of global warming and climate change[31], this stylized fact raises concerns that locust infestations could become even more frequent and severe in the future (Salih et al., 2020). To better understand the multi-faceted nature of locust ecology, as excellent studies by Chen et al. (2020) and Sun et al. (2022) suggest, we test this hypothesis empirically in a multiple regression framework.

For this purpose, we aggregate the $40,993$ grid cells of 0.25 DD size cross-sectionally from 1985 to 2020. Consistent with the locust measure in the main analysis, we employ the average number of months of locust infestation per year over the entire study period as the dependent variable. The explanatory variable of main interest is then the average annual change in yearly average ground-level temperature, as shown in Figure 7, Panel (a). As further control variables, the regression includes measures of geographic location, terrain characteristics, the SPEI drought index, average precipitation, a land suitability for agriculture index, as well as a full set of country fixed effects to account for unobserved country-specific factors. The estimates suggest that a temperature increase of one degree Celsius over the next 36 years is associated with a 0.398 additional month of locust infestation per year ($Std.\ Err. = 0.027$; Adjusted $R^2 = 0.208$).[32]

The relationship established in this regression allows us to quantify the impact of additional locust occurrences induced by global warming on accumulated years of schooling. Successfully limiting the maximum temperature increase to the 1.5 $^{\circ}C$ goal defined in the Paris Agreement (Raftery et al., 2017) would imply, on average, $1.5 \times 0.417 \approx 0.626$ additional locust-affected months per year. When applied to our results, this would translate into $2 \times 0.626 \approx .1.252$ additional locust events for each 24-month time bin. This would imply

[31] See Peng et al. (2020) for a review of how historical locust occurrences may be linked to global warming.

[32] See Table C2 in the supplemental material to this paper for a detailed description of the empirical results.



(a) Temperature Anomalies

(b) Total Locust Infestations

Figure 7: Locust Ecology Maps

Notes: This map visualizes the spatial distribution of temperature anomalies, Panel (a), and locust infestations, Panel (b), during the period 1985-2020. Locust infestations include both locust swarms and bands. For clarity of presentation, the data are aggregated to rectangular grid cells of 0.25 DD size. See the main text for additional details.

an approximately 1.20 year decrease in *years of education* over a 10-year period.[33] This effect is very sizable and illustrates an additional threat to rural livelihoods emanating from climate change.

6 Conclusion

This paper examined the effects of locust infestations in Africa on households' educational decisions. The findings imply that school-aged individuals in farming households, ceteris paribus, have a higher likelihood to leave school after locust outbreaks than individuals in non-farming households. A monthly locust episode that occurred three to four years before the DHS survey interview date was linked to an increase in the dropout rate of roughly 1.31 percentage points. Comparable effects appear for events up to 10 years in the past, demonstrating a long-lasting effect on farming households.

The analyses reveal that the effects of locust outbreaks differ across age groups. School dropout decisions tend to be affected in individuals over 15 years of age, whereas school enrollment tends to be delayed

[33] The estimated effect is based on Column (7) of Table C3 in the supplemental material to this paper and is calculated by summing up the regression coefficients of each locust treatment bin $a \in \mathbb{B}$ interacted with the farming status variable and then multiplying this by the increase of 1.252 locust-affected months per bin, so that $(-0.1985 + (-0.4015) + (-0.1489) + (-0.4523)) \times 1.252 \approx -1.2012$.

in younger children. Such effects are likely to be exacerbated in households with low educational levels. Further heterogeneous effects are observed among girls and young women, who are affected disproportionately by locust outbreaks. In addition, the results show that the potential transmission mechanism of locust shocks is more akin to an income shock. Compared to children from more affluent households, children from poorer households and households with large farms are more adversely affected by historical locust outbreaks. This shows an increased risk of crop loss during locust outbreaks, leading to immediate economic losses. Overall, these observations highlight the severe risk climate change poses to educational, gender, and income inequalities in African countries. We also contributed in terms of rising global temperatures and future occurrences of locusts and their impact on schooling. We found that, on average, a permanent 1.5 $^{\circ}C$ increase in global temperature will lead to ≈ 0.626 additional locust-affected months per year, which transcends to a decrease in years of education by about 1.2 years over a period of 10 years.

Our findings provide valuable information about agricultural productivity and the mitigation of weather-induced shocks in the study areas, and are also relevant to other African regions. In the absence of control measures or projects that cushion the impacts of plagues, school-aged children from agricultural households have a higher probability of being withdrawn from school or accumulating less education due to income losses triggered by crop failure. Farming households are highly vulnerable, since they have a limited capacity to control desert locusts (Amare et al., 2021). As locust shocks are the most significant and damaging crop pest, according to (FAO, 2009), they typically reduce the capacity of agricultural households to farm successfully in severely affected regions. The best course of action is to improve the factors that facilitate locust control, including effective communication measures, good infrastructure (such as road networks in remote locations), and funding to support the development of skilled employees for locust control operations. Governments should also allocate funding to risk-reduction products (pesticides, spraying equipment, or mass spraying for small and large farmers). Furthermore, safety measures should be implemented for agricultural households to prevent revenue fluctuations and the loss of livelihoods during locust outbreaks. In the absence of regulatory mechanisms or insurable markets for natural shocks in these regions, incomes in rural areas will fall and the wealth gap between the rich and the poor will grow. Public investments should therefore be made in installing systems to lessen the possibility of desert locust outbreaks. It is also essential that governments emphasize and adhere to climate change policies to prevent an upsurge in locust occurrences and other repercussions of climate change. These initiatives will encourage people to engage in agricultural production and aid in addressing the world's food shortages and hunger (Oskorouchi and Sousa-Poza, 2021).

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A Summary Statistics

Table A1: Summary Statistics Across Age Groups – Total Sample

	Locust Treatment Bins: Mean (SD)					Currently in School		Years of Schooling	
Age	1-24	25-48	49-72	73-96	97-120	Mean (SD)	Obs.	Mean (SD)	Obs.
3	0 (0.024)	0 (0)	0 (0)	0 (0)	0 (0)	3.516 (18.418)	141,414	0.001 (0.062)	140,991
4	0.018 (0.193)	0 (0)	0 (0)	0 (0)	0 (0)	6.884 (25.318)	138,087	0.003 (0.100)	137,842
5	0.015 (0.178)	0.004 (0.077)	0 (0)	0 (0)	0 (0)	26.275 (44.013)	127,323	0.064 (0.342)	125,743
6	0.020 (0.200)	0.029 (0.256)	0 (0)	0 (0)	0 (0)	45.540 (49.801)	144,129	0.206 (0.554)	143,286
7	0.020 (0.201)	0.029 (0.255)	0.005 (0.090)	0 (0)	0 (0)	64.319 (47.906)	139,300	0.555 (0.846)	138,801
8	0.021 (0.209)	0.030 (0.258)	0.021 (0.182)	0 (0)	0 (0)	73.288 (44.246)	137,711	1.038 (1.116)	137,381
9	0.018 (0.191)	0.030 (0.255)	0.021 (0.175)	0.047 (0.340)	0 (0)	80.509 (39.614)	113,819	1.644 (1.361)	113,590
10	0.021 (0.206)	0.029 (0.253)	0.022 (0.184)	0.088 (0.457)	0 (0)	78.848 (40.839)	136,636	2.144 (1.657)	136,353
11	0.016 (0.176)	0.029 (0.247)	0.020 (0.171)	0.072 (0.415)	0.048 (0.394)	83.839 (36.809)	97,860	2.920 (1.854)	97,659
12	0.020 (0.201)	0.029 (0.252)	0.022 (0.181)	0.083 (0.439)	0.115 (0.560)	79.857 (40.107)	123,400	3.361 (2.160)	123,171
13	0.022 (0.210)	0.031 (0.266)	0.024 (0.189)	0.082 (0.447)	0.117 (0.568)	78.691 (40.950)	111,922	4.018 (2.425)	111,707
14	0.018 (0.192)	0.029 (0.244)	0.020 (0.174)	0.080 (0.442)	0.124 (0.590)	76.412 (42.455)	99,480	4.709 (2.688)	99,255
15	0.020 (0.201)	0.031 (0.255)	0.024 (0.193)	0.076 (0.437)	0.128 (0.595)	70.317 (45.686)	89,793	5.187 (2.998)	89,605
16	0.021 (0.208)	0.035 (0.271)	0.022 (0.182)	0.076 (0.438)	0.128 (0.609)	65.983 (47.377)	80,751	5.862 (3.204)	80,544
17	0.019 (0.193)	0.034 (0.262)	0.022 (0.180)	0.078 (0.438)	0.140 (0.645)	57.682 (49.407)	76,030	6.245 (3.561)	75,832
18	0.024 (0.221)	0.037 (0.286)	0.024 (0.192)	0.085 (0.457)	0.141 (0.635)	45.772 (49.821)	88,578	6.340 (3.930)	88,288
19	0.018 (0.193)	0.042 (0.295)	0.021 (0.178)	0.066 (0.410)	0.127 (0.596)	39.338 (48.850)	62,886	6.976 (4.008)	62,702
20	0.028 (0.236)	0.045 (0.311)	0.027 (0.206)	0.095 (0.483)	0.144 (0.623)	27.071 (44.433)	86,481	6.192 (4.574)	86,139
21	0.017 (0.187)	0.046 (0.305)	0.021 (0.175)	0.065 (0.412)	0.121 (0.583)	26.382 (44.071)	52,858	7.286 (4.430)	52,731
22	0.021 (0.208)	0.043 (0.297)	0.024 (0.189)	0.082 (0.451)	0.144 (0.633)	19.150 (39.349)	63,691	6.693 (4.757)	63,457
23	0.021 (0.206)	0.046 (0.311)	0.025 (0.194)	0.073 (0.435)	0.137 (0.622)	16.306 (36.943)	55,187	7.011 (4.812)	54,981
24	0.023 (0.214)	0.045 (0.308)	0.024 (0.192)	0.073 (0.430)	0.138 (0.618)	12.839 (33.453)	50,516	6.955 (4.925)	50,330

Notes: The means are reported with the standard deviations in parentheses. The observations (obs.) differ slightly for years of schooling due to missing data. This table presents descriptive statistics for all individuals in the sample for both treated and non-treated across age groups. Currently in school indicates individuals between the ages of 3 and 24 who are still in school prior to the DHS interview date. It is scaled to 100, i.e., either 0 when the individual reports not being in school or 100 for being in school. See the main text for additional details on data construction and sources.

Table A2: Summary Statistics Across Age Groups – Treated Sample

	Locust Treatment Bins: Mean (SD)					Currently in School		Years of Schooling	
Age	1-24	25-48	49-72	73-96	97-120	Mean (SD)	Obs.	Mean (SD)	Obs.
3	1.792 (0.415)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	24	0 (0)	24
4	1.754 (0.724)	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	1,437	0 (0)	1,436
5	1.388 (0.976)	0.358 (0.639)	0 (0)	0 (0)	0 (0)	25.230 (43.448)	1,415	0.030 (0.201)	1,385
6	0.811 (1.006)	1.210 (1.129)	0 (0)	0 (0)	0 (0)	43.164 (49.538)	3,489	0.066 (0.296)	3,476
7	0.754 (0.989)	1.085 (1.147)	0.177 (0.526)	0 (0)	0 (0)	67.538 (46.830)	3,672	0.349 (0.606)	3,664
8	0.522 (0.900)	0.729 (1.062)	0.528 (0.743)	0 (0)	0 (0)	71.742 (45.029)	5,602	0.880 (0.963)	5,595
9	0.317 (0.732)	0.521 (0.931)	0.356 (0.641)	0.804 (1.179)	0 (0)	73.083 (44.356)	6,587	1.445 (1.271)	6,580
10	0.267 (0.684)	0.360 (0.829)	0.278 (0.594)	1.112 (1.223)	0 (0)	66.756 (47.111)	10,847	1.789 (1.613)	10,817
11	0.182 (0.572)	0.339 (0.775)	0.232 (0.538)	0.833 (1.168)	0.556 (1.234)	72.237 (44.786)	8,432	2.564 (1.948)	8,417
12	0.156 (0.543)	0.228 (0.673)	0.170 (0.479)	0.652 (1.067)	0.900 (1.321)	67.435 (46.863)	15,787	2.940 (2.304)	15,757
13	0.173 (0.565)	0.244 (0.708)	0.185 (0.498)	0.636 (1.099)	0.910 (1.341)	66.276 (47.278)	14,349	3.491 (2.661)	14,291
14	0.145 (0.521)	0.228 (0.652)	0.160 (0.466)	0.634 (1.090)	0.974 (1.384)	64.371 (47.892)	12,630	4.145 (3.049)	12,588
15	0.153 (0.543)	0.240 (0.676)	0.188 (0.510)	0.596 (1.084)	0.994 (1.377)	58.599 (49.257)	11,524	4.447 (3.353)	11,473
16	0.162 (0.556)	0.270 (0.709)	0.172 (0.480)	0.584 (1.084)	0.986 (1.415)	57.566 (49.427)	10,508	5.200 (3.717)	10,462
17	0.138 (0.510)	0.252 (0.673)	0.162 (0.467)	0.576 (1.065)	1.038 (1.467)	50.837 (49.995)	10,272	5.504 (4.138)	10,236
18	0.176 (0.569)	0.266 (0.725)	0.175 (0.489)	0.611 (1.087)	1.014 (1.420)	41.586 (49.289)	12,319	5.395 (4.449)	12,252
19	0.143 (0.525)	0.329 (0.771)	0.169 (0.473)	0.520 (1.046)	1 (1.391)	38.693 (48.708)	7,960	6.346 (4.746)	7,912
20	0.183 (0.581)	0.294 (0.750)	0.176 (0.503)	0.622 (1.099)	0.949 (1.338)	26.243 (43.997)	13,154	5.109 (5.052)	13,072
21	0.135 (0.508)	0.359 (0.783)	0.165 (0.465)	0.506 (1.049)	0.943 (1.369)	27.318 (44.563)	6,772	6.676 (5.370)	6,756
22	0.144 (0.529)	0.296 (0.731)	0.164 (0.473)	0.567 (1.063)	0.996 (1.385)	18.339 (38.701)	9,226	5.686 (5.404)	9,184
23	0.154 (0.535)	0.335 (0.775)	0.180 (0.494)	0.525 (1.063)	0.993 (1.396)	14.585 (35.298)	7,638	6.086 (5.587)	7,609
24	0.162 (0.548)	0.320 (0.762)	0.172 (0.485)	0.514 (1.038)	0.977 (1.372)	10.738 (30.962)	7,152	5.903 (5.592)	7,113

Notes: The means are reported with the standard deviations in parentheses. The observations (obs.) differ slightly for years of schooling due to missing data. This table presents descriptive statistics for all individuals in the sample for both treated and non-treated across age groups. Currently in school indicates individuals between the ages of 3 and 24 who are still in school prior the the DHS interview date. It is scaled to 100, i.e., either 0 when the individual reports not being in school or 100 for being in school. See the main text for additional details on data construction and sources.

Table A3: Summary Statistics Across Age Groups – Non-Treated Sample

	Locust Treatment Bins: Mean (SD)					Currently in School		Years of Schooling	
Age	1-24	25-48	49-72	73-96	97-120	Mean (SD)	Obs.	Mean (SD)	Obs.
3	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	3.517 (18.420)	141,390	0.001 (0.062)	140,967
4	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	6.956 (25.441)	136,650	0.003 (0.101)	136,406
5	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	26.287 (44.019)	125,908	0.064 (0.344)	124,358
6	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	45.599 (49.806)	140,640	0.210 (0.558)	139,810
7	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	64.232 (47.932)	135,628	0.561 (0.851)	135,137
8	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	73.353 (44.211)	132,109	1.045 (1.121)	131,786
9	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	80.965 (39.258)	107,232	1.656 (1.365)	107,010
10	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	79.891 (40.082)	125,789	2.175 (1.657)	125,536
11	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	84.933 (35.773)	89,428	2.953 (1.841)	89,242
12	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	81.679 (38.684)	107,613	3.423 (2.132)	107,414
13	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	80.516 (39.608)	97,573	4.096 (2.379)	97,416
14	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	78.164 (41.314)	86,850	4.790 (2.621)	86,667
15	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	72.043 (44.879)	78,269	5.296 (2.926)	78,132
16	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	67.242 (46.933)	70,243	5.961 (3.108)	70,082
17	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	58.752 (49.228)	65,758	6.361 (3.448)	65,596
18	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	46.448 (49.874)	76,259	6.493 (3.817)	76,036
19	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	39.431 (48.871)	54,926	7.067 (3.882)	54,790
20	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	27.219 (44.509)	73,327	6.386 (4.455)	73,067
21	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	26.244 (43.997)	46,086	7.376 (4.267)	45,975
22	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	19.288 (39.456)	54,465	6.864 (4.617)	54,273
23	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	16.583 (37.193)	47,549	7.160 (4.658)	47,372
24	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	13.186 (33.834)	43,364	7.128 (4.784)	43,217

Notes: The means are reported with the standard deviations in parentheses. The observations (obs.) slightly differ for years of schooling due to missing data. This table presents descriptive statistics for all individuals in the sample for both treated and non-treated across age groups. Currently in school indicates individuals between the ages of 3 and 24 who are still in school prior to the DHS interview date. It is scaled to 100, i.e., either 0 when the individual reports not being in school or 100 for being in school. See the main text for additional details on data construction and sources.

Table A4: Summary Statistics for the Main Regression Variables

	Total Sample Obs.: 2,217,852				Treated Sample Obs.: 180,796				Non-Treated Sample Obs.: 2,037,056			
Variables	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.
	Panel A: Dependent variables											
Currently in School (Ages 3-24)	51.344	49.982	0	100	49.723	49.999	0	100	51.488	49.978	0	100
Years of Schooling	3.094	3.681	0	24	4.086	4.148	0	24	3.006	3.624	0	24
	Panel B: Locust treatment variables											
$TM^{\overline{50}km}_{idct[f(1-24)]}$	0.019	0.195	0	5	0.230	0.645	0	5	0	0	0	0
$TM^{\overline{50}km}_{idct[f(25-48)]}$	0.027	0.243	0	4	0.337	0.789	0	4	0	0	0	0
$TM^{\overline{50}km}_{idct[f(49-72)]}$	0.016	0.155	0	3	0.194	0.510	0	3	0	0	0	0
$TM^{\overline{50}km}_{idct[f(73-96)]}$	0.048	0.346	0	6	0.591	1.072	0	6	0	0	0	0
$TM^{\overline{50}km}_{idct[f(97-120)]}$	0.063	0.426	0	8	0.773	1.296	0	8	0	0	0	0
$TM^{\overline{50}km}_{idct[f(1-24)]} \times Farmer_{hd}$	0.010	0.139	0	4	0.121	0.473	0	4	0	0	0	0
$TM^{\overline{50}km}_{idct[f(25-48)]} \times Farmer_{hd}$	0.010	0.152	0	4	0.124	0.520	0	4	0	0	0	0
$TM^{\overline{50}km}_{idct[f(49-72)]} \times Farmer_{hd}$	0.011	0.128	0	3	0.133	0.430	0	3	0	0	0	0
$TM^{\overline{50}km}_{idct[f(73-96)]} \times Farmer_{hd}$	0.032	0.286	0	6	0.395	0.926	0	6	0	0	0	0
$TM^{\overline{50}km}_{idct[f(97-120)]} \times Farmer_{hd}$	0.035	0.334	0	8	0.424	1.097	0	8	0	0	0	0
	Panel C: Farming indicators											
Farmer	0.692	0.462	0	1	0.557	0.497	0	1	0.704	0.456	0	1
Small Farm	0.080	0.272	0	1	0.011	0.103	0	1	0.087	0.281	0	1
Medium Farm	0.084	0.277	0	1	0.036	0.187	0	1	0.088	0.283	0	1
Large Farm	0.459	0.498	0	1	0.458	0.498	0	1	0.459	0.498	0	1
	Panel D: Geographic controls											
Absolute Latitude	10.940	7.073	0	31.566	16.084	7.264	2.535	31.566	10.484	6.872	0	31.566
Absolute Longitude	21.414	12.696	0.001	50.247	22.513	12.771	0.025	47.008	21.316	12.685	0.001	50.247
ln(0.01 + Distance to Border)	3.782	1.337	-4.297	6.387	4.004	1.341	-4.297	6.108	3.762	1.335	-4.297	6.387
ln(0.01 + Distance to Coast)	5.632	1.365	-2.572	7.467	5.176	1.299	-2.158	7.449	5.672	1.364	-2.572	7.467
ln(0.01 + Distance to River)	2.746	1.355	-4.581	6.909	2.981	1.562	-4.526	6.761	2.726	1.333	-4.581	6.909
ln(0.01 + Distance to Capital)	5.295	1.179	-2.719	7.555	5.185	1.213	0.153	7.108	5.305	1.176	-2.719	7.555
ln(0.01 + Distance to Nearest Settlement)	4.102	1.330	-3.269	6.950	3.739	1.556	-2.321	6.614	4.134	1.303	-3.269	6.950
ln(0.01 + Distance to Nearest Catholic Church)	4.160	1.074	-1.406	7.271	4.029	1.235	-1.214	7.271	4.171	1.057	-1.406	7.271
ln(0.01 + Distance to Nearest Protestant Church)	4.765	1.306	-1.713	7.331	5.265	1.331	-0.328	7.297	4.720	1.295	-1.713	7.331
ln(0.01 + Distance to Railroad Line)	3.517	1.888	-4.596	7.037	3.063	2.293	-4.579	6.920	3.558	1.843	-4.596	7.037
ln(0.01 + Distance to Road Line)	0.693	1.495	-4.604	5.676	0.302	1.357	-4.486	4.934	0.728	1.501	-4.604	5.676
	Panel F: Land productivity controls											
Land Suitability for Agriculture	0.442	0.257	0.001	0.999	0.254	0.283	0.001	0.997	0.458	0.248	0.001	0.999
Range of Cropland Area	0.215	0.253	0	1	0.249	0.250	0	1	0.212	0.253	0	1
Share of Pastureland	0.228	0.274	0	1	0.223	0.251	0	1	0.229	0.276	0	1
Mean of Elevation	699.752	640.125	-90.750	3460.250	481.641	727.964	-34.424	3460.250	719.110	628.091	-90.750	3460.250
Standard Deviation of Elevation	46.529	62.433	0.283	600.418	41.484	67.476	0.327	483.453	46.977	61.946	0.283	600.418
	Panel G: Socioeconomic controls											
$\ln(0.01 + NightLight_{d,c,t})$	-0.013	5.501	-4.605	9.186	2.416	5.779	-4.605	9.112	-0.229	5.423	-4.605	9.186
$\ln(0.01 + Population_{d,c,t})$	9.822	1.776	-4.605	15.418	10.150	2.159	-4.605	15.418	9.793	1.735	-4.605	15.418
Number of Conflicts	1.258	6.413	0	170	1.390	5.563	0	170	1.247	6.483	0	170
	Panel H: Weather controls											
Mean Temperature	24.477	3.773	8.758	32.092	26.235	3.369	14.333	31.508	24.321	3.768	8.758	32.092
Mean Precipitation	104.404	65.665	0.058	333	85.481	65.296	0.400	297.183	106.083	65.434	0.058	333
Mean Potential Evapo-Transpiration	4.099	0.921	2.317	8.325	5.094	0.815	3.267	7.875	4.010	0.877	2.317	8.325
Number of Frost Days	2.187	13.323	0	170.780	1.076	2.964	0	24.080	2.286	13.870	0	170.780
SPEI Drought Index	-0.148	0.703	-2.376	2.280	-0.239	0.607	-2.032	1.289	-0.140	0.711	-2.376	2.280
	Panel I: DHS individual and household controls											
Indicator: Male Member of Household	0.495	0.500	0	1	0.486	0.500	0	1	0.496	0.500	0	1
Indicator: Son or Daughter of Head	0.656	0.475	0	1	0.646	0.478	0	1	0.657	0.475	0	1
Age of Household Member	11.630	5.994	3	24	15.276	4.897	3	24	11.306	5.976	3	24
Indicator: Male Household Head	0.763	0.426	0	1	0.812	0.390	0	1	0.758	0.428	0	1
Size of Household	6.800	2.412	1	10	7.283	2.503	1	10	6.758	2.399	1	10
Educational Level of Household Head	0.903	0.909	0	3	0.610	0.919	0	3	0.929	0.904	0	3
Household has Electricity	0.313	0.464	0	1	0.506	0.500	0	1	0.296	0.457	0	1
Household has Toilet	0.138	0.345	0	1	0.286	0.452	0	1	0.124	0.330	0	1
Household has Pipe Water	0.329	0.470	0	1	0.557	0.497	0	1	0.308	0.462	0	1
Household has Finished Floor	0.455	0.498	0	1	0.551	0.497	0	1	0.446	0.497	0	1
Household Owns a Car or Truck	0.054	0.226	0	1	0.053	0.223	0	1	0.054	0.226	0	1
Household Owns a Bicycle	0.296	0.456	0	1	0.231	0.422	0	1	0.302	0.459	0	1
Household Owns a Motorcycle or Scooter	0.163	0.369	0	1	0.144	0.351	0	1	0.165	0.371	0	1
Wealth Index-Poor	0.447	0.497	0	1	0.441	0.497	0	1	0.448	0.497	0	1
Wealth Index-Middle	0.204	0.403	0	1	0.188	0.391	0	1	0.205	0.404	0	1
Household Owns a Radio	0.586	0.493	0	1	0.603	0.489	0	1	0.584	0.493	0	1
Household Owns a Television	0.296	0.457	0	1	0.470	0.499	0	1	0.281	0.449	0	1

Notes: This table shows basic summary statistics for the main variables employed in the regression analysis. See the main text for additional details on data construction and sources.

B Data Description

Table B1: Detailed Description of DHS Variables

Variable	Description
Currently Being in School	Dummy for being in school. The variable is constructed using DHS variables "school enrollment status (hv129)", "household member is still in school (hv110)", and "household member attended school during current school year (hv121)". The variable equals one if hv110 equals one, hv121 equals one or two, hv129 equals one, two or three, and zero otherwise.
Years of Schooling	The variable is based on the DHS variables "highest years of education completed (hv107)" and "individual's education in single years (hv108)". The variable is equal to hv108 if the individual's age is less than or equal to twenty-four. The educational questionnaire is given to individuals twenty-four years of age and younger. We also assume that if the individual started education at the age of one, the maximum education is likely to be twenty-four. Therefore, we code the variable as missing if hv107 exceeds twenty-four years.
Farmer	An indicator for owning agricultural land. The variable is based on whether the household owns land suitable for agriculture (hv244).
Small Farm Size	Dummy equals one if hectares of agricultural land (hv245) is between one and two.
Medium Farm Size	Same as above but equal to one if hv245 is greater than five hectares.
Large Farm Size	Same as above but equal to one if hv245 is greater than five hectares.
Wealth Index	The variable is based on the wealth index (hv270) calculated by DHS. The principal component analysis calculates the total standard of living for households. It is determined using data on possessions of basic amenities (water, sanitation facilities), asset ownership (such as land, cattle, cars, televisions, and radios), and the sort of building materials used to construct the residence (wall, floor, roof type). In the case of an economic shock, the wealth index places people on continuous, country-specific five-scale quintiles of relative wealth, allowing comparisons between those from richer and poorer households. We combine the poor and poorest and classify them as "poor" as well as the rich and richest as "rich" (the "rich" is the base category for the regression). Nevertheless, the "middle" remain unchanged. For more details on how the DHS wealth index is constructed, see: https://dhsprogram.com/programming/wealth%20index/Steps_to_constructing_the_new_DHS_Wealth_Index.pdf.
Household has Electricity	An indicator equals one if the household has electricity (hv206).
Household has Toilet	A dummy equals one if the household has a flush toilet. It is generated from the type of toilet facility in the household, which is country specific. Therefore we take the major categories which are standard across countries. That is, if hv205 is equal to ten.
Household has Access to Piped Water	A dummy equals one if the household main source of drinking water is pipe water based on the question "main source of drinking water for members of the household (hv201)". We also use the major categories (e.g., pipe, tube well, bottled, rainwater).
Household has Finished Floor	A dummy one if the main floor material is a finished material type (e.g., tile, polished floor). The variable is based on the main floor material (hv213), which is country-specific, but we use the major categories (i.e., natural, rudimentary, and finished). That is when hv213 equals thirty.
Household Owns Car/Truck	A dummy equals one if the household has a car/truck (based on "has car/truck (hv212)").
Household Owns Bicycle	A dummy equals one if the household has a bicycle (based on "has bicycle (hv210)").
Household Owns Motorcycle/Scooter	A dummy equals one if the household has a motorcycle/scooter (based on "has motorcycle/scooter (hv211)").
Household Owns Radio	A dummy equals one if the household has a radio (based on whether "household has radio (hv207)").
Household Owns Television	A dummy equals one if the household has television (based on whether "household has television (hv208)").
Male Member of the Household	An indicator equals one if the household member is male (based on the reported "sex of household member (hv104)").
Age of Household Member	Age of household member (based on the reported "age of the individual (hv105)").
Male Head	A dummy equals one if household head is male (based on reported "sex of head of household (hv219)").
Size of the Household	A dummy that equals one for each household size category 1 to 10 persons (based on "number of household members (hv009)"). The last category also includes households with more than 10 persons.
Son or Daughter	An indicator equals one if the member of the household is a son or daughter of the head. It is based on the "relationship to head (hv101)" questionnaire. Equals one if hv101 is equal to three.
Educational Level of Head	It is constructed using the highest educational level attained (hv106) and relationship to head; one is household head (hv101). It is categorized as no education, primary, secondary and higher.

Notes: The table shows detailed description of all the DHS variables used in our analysis. The variables can be found in the household record (PR) of the DHS program data types.

Table B2: DHS Survey Version/Year

	DHS Version/Year										
Countries	**8B/2019**	**81/2019**	**7A/2019**	**81/2018**	**7A/2018**	**7B/2018**	**71/2018**	**7Z/2017**	**71/2017**	**7B/2016**	**7I/2016**
Angola	–	–	–	–	–	–	–	–	–	–	–
Burkina Faso	–	–	–	–	–	–	–	–	–	–	–
Benin	–	–	–	–	–	–	–	–	35,014 (488)	–	–
Burundi	–	–	–	–	–	–	–	–	–	–	–
Congo Democratic Republic	–	–	–	–	–	–	–	–	–	–	–
Cote d'Ivoire	–	–	–	–	–	–	–	–	–	–	–
Cameroon	–	–	–	–	–	–	30,433 (422)	–	–	–	–
Egypt	–	–	–	–	–	–	–	–	–	–	–
Ethiopia	–	21,447 (301)	–	–	–	–	–	–	–	–	–
Gabon	–	–	–	–	–	–	–	–	–	–	–
Ghana	–	–	–	–	–	–	–	–	–	–	–
Guinea	–	–	–	–	–	–	24,045 (355)	–	–	–	–
Kenya	–	–	–	–	–	–	–	–	–	–	–
Liberia	–	–	9,314 (149)	–	–	–	–	–	–	–	–
Lesotho	–	–	–	–	–	–	–	–	–	–	–
Madagascar	–	–	–	–	–	–	–	–	–	–	–
Mali	–	–	–	–	27,488 (327)	–	–	–	–	–	–
Malawi	–	–	–	–	–	–	–	–	–	–	–
Mozambique	–	–	–	–	–	–	–	–	–	–	–
Nigeria	–	–	–	–	–	91,026 (1,349)	–	–	–	–	–
Niger	–	–	–	–	–	–	–	–	–	–	–
Namibia	–	–	–	–	–	–	–	–	–	–	–
Rwanda	–	7,213 (125)	–	–	–	–	–	–	–	–	–
Sierra Leone	–	–	30,690 (450)	–	–	–	–	–	–	–	–
Senegal	19,212 (188)	–	–	20,017 (186)	–	–	–	36,816 (344)	–	–	19,763 (185)
Swaziland	–	–	–	–	–	–	–	–	–	–	–
Chad	–	–	–	–	–	–	–	–	–	–	–
Togo	–	–	–	–	–	–	–	–	–	–	–
Tanzania	–	–	–	–	–	–	–	–	–	–	–
Uganda	–	–	–	–	–	–	–	–	–	47,818 (641)	–
Zambia	–	–	–	–	–	–	34,531 (519)	–	–	–	–
Zimbabwe	–	–	–	–	–	–	–	–	–	–	–
Total	19,212 (188)	28,660 (426)	40,004 (559)	20,017 (186)	27,488 (327)	91,026 (1,349)	89,009 (1,296)	36,816 (344)	35,014 (488)	47,818 (641)	19,763 (185)

Notes: The table shows the number of individuals and survey locations (in parentheses) by country, version, and year of the DHS survey included in our sample. – denote missing data.

Table B2: *Continued*

	DHS Version/Year										
Countries	**71/2016**	**7A/2015**	**7B/2015**	**7H/2015**	**72/2015**	**71/2015**	**6R/2014**	**72/2014**	**71/2014**	**70/2014**	**61/2014**
Angola	–	–	–	–	–	33,711 (532)	–	–	–	–	–
Burkina Faso	–	–	–	–	–	–	–	–	–	–	–
Benin	–	–	–	–	–	–	–	–	–	–	–
Burundi	42,282 (545)	–	–	–	–	–	–	–	–	–	–
Congo Democratic Republic	–	–	–	–	–	–	–	–	–	–	–
Cote d'Ivoire	–	–	–	–	–	–	–	–	–	–	–
Cameroon	–	–	–	–	–	–	–	–	–	–	–
Egypt	–	–	–	–	–	–	–	–	–	–	44,762 (1,521)
Ethiopia	38,372 (619)	–	–	–	–	–	–	–	–	–	–
Gabon	–	–	–	–	–	–	–	–	–	–	–
Ghana	–	–	–	–	–	–	–	20,196 (394)	–	–	–
Guinea	–	–	–	–	–	–	–	–	–	–	–
Kenya	–	–	–	–	–	–	–	78,440 (1,524)	–	–	–
Liberia	–	–	–	–	–	–	–	–	–	–	–
Lesotho	–	–	–	–	–	–	–	–	19,600 (399)	–	–
Madagascar	–	–	–	–	–	–	–	–	–	–	–
Mali	–	–	–	–	–	–	–	–	–	–	–
Malawi	–	66,316 (819)	–	–	–	–	–	–	–	–	–
Mozambique	–	–	–	–	–	16,289 (272)	–	–	–	–	–
Nigeria	–	–	–	–	–	–	–	–	–	–	–
Niger	–	–	–	–	–	–	–	–	–	–	–
Namibia	–	–	–	–	–	–	–	–	–	–	–
Rwanda	–	–	–	–	–	–	–	–	–	26,390 (457)	–
Sierra Leone	–	–	–	–	–	–	–	–	–	–	–
Senegal	–	–	–	19,334 (187)	–	–	18,881 (176)	–	–	18,881 (176)	–
Swaziland	–	–	–	–	–	–	–	–	–	–	–
Chad	–	–	–	–	–	–	–	–	55,276 (623)	–	–
Togo	–	–	–	–	–	–	–	–	–	–	–
Tanzania	–	–	28,565 (513)	–	–	–	–	–	–	–	–
Uganda	–	–	–	–	–	–	–	–	–	–	–
Zambia	–	–	–	–	–	–	–	–	–	–	–
Zimbabwe	–	–	–	–	22,311 (400)	–	–	–	–	–	–
Total	80,654 (1,164)	66,316 (819)	28,565 (513)	19,334 (187)	22,311 (400)	50,000 (804)	18,881 (176)	98,636 (1,918)	74,876 (1,022)	45,271 (633)	44,762 (1,521)

Notes: The table shows the number of individuals and survey locations (in parentheses) by country, version, and year of the DHS survey included in our sample. – denote missing data.

Table B2: *Continued*

Countries	DHS Version/Year										
	6A/2013	**61/2013**	**6A/2012**	**6D/2012**	**6R/2012**	**62/2012**	**61/2012**	**62/2011**	**61/2011**	**6A/2010**	**63/2010**
Angola	–	–	–	–	–	–	–	–	–	–	–
Burkina Faso	–	–	–	–	–	–	–	–	–	–	–
Benin	–	–	–	–	–	–	42,650 (656)	–	–	–	–
Burundi	–	–	–	–	–	–	–	–	–	–	–
Congo Democratic Republic	–	46,742 (481)	–	–	–	–	–	–	–	–	–
Cote d'Ivoire	–	–	–	–	–	23,583 (315)	–	–	–	–	–
Cameroon	–	–	–	–	–	–	–	–	36,556 (570)	–	–
Egypt	–	–	–	–	–	–	–	–	–	–	–
Ethiopia	–	–	–	–	–	–	–	–	–	–	–
Gabon	–	–	–	–	–	–	14,512 (252)	–	–	–	–
Ghana	–	–	–	–	–	–	–	–	–	–	–
Guinea	–	–	–	–	–	21,218 (262)	–	–	–	–	–
Kenya	–	–	–	–	–	–	–	–	–	–	–
Liberia	–	–	–	–	–	–	–	–	–	–	–
Lesotho	–	–	–	–	–	–	–	–	–	–	–
Madagascar	–	–	–	–	–	–	–	–	–	–	–
Mali	–	–	30,867 (411)	–	–	–	–	–	–	–	–
Malawi	–	–	–	–	–	–	–	–	–	–	–
Mozambique	–	–	–	–	–	–	–	30,012 (546)	–	–	–
Nigeria	84,269 (859)	–	–	–	–	–	–	–	–	–	–
Niger	–	–	–	–	–	–	34,632 (476)	–	–	–	–
Namibia	–	18,251 (515)	–	–	–	–	–	–	–	–	–
Rwanda	–	–	–	–	–	–	–	–	–	–	–
Sierra Leone	–	32,792 (355)	–	–	–	–	–	–	–	–	–
Senegal	–	–	–	19,755 (176)	19,755 (176)	–	–	–	–	–	–
Swaziland	–	–	–	–	–	–	–	–	–	–	–
Chad	–	–	–	–	–	–	–	–	–	–	–
Togo	–	23,339 (315)	–	–	–	–	–	–	–	–	–
Tanzania	–	–	24,022 (503)	–	–	–	–	–	–	–	20,390 (375)
Uganda	–	–	–	–	–	–	–	–	24,218 (387)	28,408 (452)	–
Zambia	–	44,013 (694)	–	–	–	–	–	–	–	–	–
Zimbabwe	–	–	–	–	–	–	–	–	–	–	–
Total	84,269 (859)	165,137 (2,360)	54,889 (914)	19,755 (176)	19,755 (176)	44,801 (577)	91,794 (1,384)	30,012 (546)	60,774 (957)	28,408 (452)	20,390 (375)

Notes: The table shows the number of individuals and survey locations (in parentheses) by country, version, and year of the DHS survey included in our sample. – denote missing data.

Table B2: *Continued*

Countries	DHS Version/Year										
	62/2010	**61/2010**	**61/2009**	**5A/2008**	**53/2008**	**52/2008**	**51/2008**	**51/2007**	**52/2006**	**52/2005**	**Total**
Angola	–	–	–	–	–	–	–	–	–	–	33,711 (532)
Burkina Faso	41,145 (541)	–	–	–	–	–	–	–	–	–	41,145 (541)
Benin	–	–	–	–	–	–	–	–	–	–	77,664 (1,144)
Burundi	–	22,127 (370)	–	–	–	–	–	–	–	–	64,409 (915)
Congo Democratic Republic	–	–	–	–	–	–	–	–	–	–	46,742 (481)
Cote d'Ivoire	–	–	–	–	–	–	–	–	–	–	23,583 (315)
Cameroon	–	–	–	–	–	–	–	–	–	–	66,989 (992)
Egypt	–	–	–	37,937 (1,066)	–	–	–	–	–	–	82,699 (2,587)
Ethiopia	–	39,986 (568)	–	–	–	–	–	–	–	–	99,805 (1,488)
Gabon	–	–	–	–	–	–	–	–	–	–	14,512 (252)
Ghana	–	–	–	21,688 (373)	–	–	–	–	–	–	41,884 (767)
Guinea	–	–	–	–	–	–	–	–	–	–	45,263 (617)
Kenya	–	–	–	–	–	19,521 (381)	–	–	–	–	97,961 (1,905)
Liberia	–	–	–	–	–	–	–	–	–	–	9,314 (149)
Lesotho	–	–	21,794 (395)	–	–	–	–	–	–	–	41,394 (794)
Madagascar	–	–	–	–	–	–	41,465 (545)	–	–	–	41,465 (545)
Mali	–	–	–	–	–	–	–	–	–	–	58,355 (738)
Malawi	–	62,801 (819)	–	–	–	–	–	–	–	–	129,117 (1,638)
Mozambique	–	–	–	–	–	–	–	–	–	–	46,301 (818)
Nigeria	–	–	–	–	74,066 (865)	–	–	–	–	–	249,361 (3,073)
Niger	–	–	–	–	–	–	–	–	–	–	34,632 (476)
Namibia	–	–	–	–	–	–	–	–	19,071 (469)	–	37,322 (984)
Rwanda	–	27,754 (461)	–	–	–	–	–	–	–	–	61,357 (1,043)
Sierra Leone	–	–	–	–	–	–	16,064 (267)	–	–	–	79,546 (1,072)
Senegal	–	35,595 (336)	–	–	–	–	–	–	–	–	228,009 (2,130)
Swaziland	–	–	–	–	–	–	–	–		–	11,851 (270)
Chad	–	–	–	–	–	–	–	–	–	–	55,276 (623)
Togo	–	–	–	–	–	–	–	–	–	–	23,339 (315)
Tanzania	–	–	–	–	–	–	–	17,650 (380)	–	–	90,627 (1,771)
Uganda	–	–	–	–	–	–	–	–	22,961 (331)	–	123,405 (1,811)
Zambia	–	–	–	–	–	–	–	18,124 (311)	–	–	96,668 (1,524)
Zimbabwe	20,737 (393)	–	–	–	–	–	–	–	–	21,098 (395)	64,146 (1,188)
Total	61,882 (786)	188,263 (2,554)	21,794 (395)	59,625 (1,439)	74,066 (865)	19,521 (381)	57,529 (812)	35,774 (691)	53,883 (1,070)	21,098 (395)	2,217,852 (33,498)

Notes: The table shows the number of individuals and survey locations (in parentheses) by country, version, and year of the DHS survey included in our sample. – denote missing data.

Supplemental Material

to the paper

Locust Infestations and Individual School Dropout: Evidence from Africa

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Further Robustness Analyses

Dynamic effects of locust exposure on school status. To further explore whether locust infestations have immediate (short-run) or persistent (long-run) effects on current school enrollment status, we estimate regression equation (4) for shorter time bins (i.e., 12 months intervals) and a much longer time horizon between the DHS survey date and locust events (i.e., 20 years). Figure D1 depicts the estimated regression coefficients and the corresponding 95% confidence interval on the interaction term between the locust treatment variable and the household's farming status across the different 12-months time bins. The figure shows quite significantly that locust events occurring 3-15 years prior to the DHS survey date have a negative and statistically significant effect on school enrollment status of farming relative to non-farming households. This finding is consistent with the evidence that shocks resulting in children school dropout are largely irreversible.

Leave one country out specification Figure D3 establishes the robustness of our findings when we estimate Equation (4) by subsequently leaving out one country from the regression sample. Thus, we can rule out concerns that a single country might drive our conclusions regarding the obtained results. In addition, this analysis provides evidence that the negative effect of locust shocks on schooling is not only a phenomenon observed in a single localized area, but more broadly can be generalized to an entire region or country.

Alternative Dependent Variable: Years of Schooling

DHS individual and household controls. Table C3 replicates specifications (1) to (6) of the main results shown in Table 2 in the main paper with years of schooling as the dependent variable. In addition, the most restrictive specification including DHS survey location fixed effects (as taken from Table 3, Column (8) in the main paper) is added, as is shown in Column (7), again, with years of schooling as the dependent variable.

The results based on the alternative dependent variable are very similar to those based on school enrollment. Individuals from farming households who experienced locust outbreaks in the past (that is, 25 to 120 months prior to the survey date), have a significantly lower amount of accumulated years of schooling throughout all specifications. For example, having experienced one single locust-infested month between 25 and 48 months in the past is associated with 0.1985 less years of schooling, based on the estimates shown in Column (7).

Dynamic effects of locust exposure on accumulated years of schooling. We have established that locust outbreaks reduce current schooling enrollment, but we are also interested in estimating its aggregate impact on accumulated years of education. In Figure D2, we estimate our baseline regression equation, but this time changing the dependent variable from a binary indicator for being in school to years of schooling (i.e., a continuous dependent variable that measures the stock of accumulated years of education). Since we observe the schooling outcome only from the current schooling status of the individual, this approach lets us gauge what the outcome would be if we looked at accumulated years of education.

The corresponding estimates are shown in Figure D2. The plotted regression coefficients suggest that locust events approximately two years prior the survey interview date have no statistically significant effect on accumulated years education.[1] However, events that are further in the past exert a more significant reduction in years of schooling. Since educational attainment is a stock measure, dropping out of school as a short-term coping mechanism decreases the likelihood of returning to school (Zamand and Hyder, 2016). This implies that locust shocks may have long-term consequences on years of schooling even if shocks do not materialize in the future. Dung (2013) shows that once children drop out of school, it is difficult for them to return back to the classroom. This leads to individuals in locust-affected homes having, on average, fewer accumulated years of schooling.

Educational Level of household head. Similar to the results presented in Figure D2, we subject analysis of heterogeneous effects with regard to the level of education of the household head (see Table 4 in the main paper) to years of schooling as an alternative dependent variable. The main results are barely changed qualitatively, as we find that regardless of the household head's educational level, locust events have a long-run effect on the individual's years of education. This pronounced effect on accumulated years of schooling, is in line with our hypothesis that once an individual drop out of school, it becomes challenging to go back to school.

Locust Ecology Regression

Table C2 presents the underlying estimates of the relationship presented in Section 5.4 of the main paper, where the relationship between temperature anomalies and the occurrence of locust outbreaks is discussed. Specification (1) presents the relationship between mean annual change of ambient temperature and the mean number of locust-infested months per year, while controlling only for country fixed effects and terrain characteristics. An average change of temperature per year of $1C$ over the 36 year period is associated with, on average, 0.391 additional locust-infested months. This relationship is robust to the inclusion of a full set of factors related to locust ecology, for example, the geographic characteristics (longitude and latitude of the grid cell's centroid, Column (2)), the average of the drought index (Column (3)), an index for agricultural land suitability (Column (4)), and last, the average amount of precipitation (Column (5)). The main results are hardly affected by the stepwise inclusion of the additional controls. The estimated coefficient on the mean annual change of temperature remains significant and positive throughout all specifications and amounts to 0.417 in the full model specification in Column (5).

[1]This observation might be due to asset ownership, as households can buffer against current and transitory shocks by depleting assets or as collateral for borrowing to smooth consumption (Beegle et al., 2003).

C Regression Tables

Table C1: Locust Infestations and Individual and Years of Schooling – Heterogeneous Effects by Educational Level of Household Head

	(1)	(2)	(3)	(4)
	Educational Level of Household Head			
	No Schooling	Primary	Secondary	Higher
	Current Years of Schooling			
$TM^{\overline{50km}}_{idct[f(1-24)]} \times Farmer_{hd}$	0.0267	-0.0065	0.2572**	0.2171
	(0.0462)	(0.0596)	(0.1030)	(0.1423)
$TM^{\overline{50km}}_{idct[f(25-48)]} \times Farmer_{hd}$	-0.0915*	-0.2857***	0.0020	-0.0397
	(0.0469)	(0.0510)	(0.0541)	(0.0692)
$TM^{\overline{50km}}_{idct[f(49-72)]} \times Farmer_{hd}$	-0.3591***	-0.0334	-0.1598	-0.2510
	(0.0841)	(0.0869)	(0.1383)	(0.3351)
$TM^{\overline{50km}}_{idct[f(73-96)]} \times Farmer_{hd}$	-0.0996***	-0.1439***	-0.2112***	-0.1909
	(0.0331)	(0.0552)	(0.0525)	(0.1351)
$TM^{\overline{50km}}_{idct[f(97-120)]} \times Farmer_{hd}$	-0.2183***	-0.3864***	-0.4635***	-0.4504***
	(0.0288)	(0.0470)	(0.0512)	(0.0917)
Observations	906,163	736,350	443,145	124,577
Adjusted R^2	0.459	0.678	0.775	0.823
Number of DHS Survey Locations	29465	30953	28028	14969
Mean of Dep. Var.	2.080	3.129	4.397	5.614
Country×Region×Time FE	Yes	Yes	Yes	Yes
Geographic Controls	Yes	Yes	Yes	Yes
Land Productivity Controls	Yes	Yes	Yes	Yes
Socioeconomic Controls	Yes	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes	Yes
DHS Individual Controls	Yes	Yes	Yes	Yes
DHS Household Controls	Yes	Yes	Yes	Yes
DHS Building Controls	Yes	Yes	Yes	Yes
DHS Transportation Controls	Yes	Yes	Yes	Yes
DHS Wealth Controls	Yes	Yes	Yes	Yes
DHS Media Controls	Yes	Yes	Yes	Yes

Notes: This table shows regressions from estimating Equation (4) for different samples according to the educational level of the household head (i.e., no schooling, primary, secondary, and higher). Data are from various DHS survey years in Africa. Observations are at the survey respondents level complemented with household, DHS survey location, and aggregated geo-spatial controls. The dependent variable is the number of completed years of schooling for individuals between the ages of 3 to 24 years. $TM^{\overline{50km}}_{idct(a)} \times Farmer_{hd}$ is a age-specific locust treatment indicator that counts the number of locust infested months during time bin $a \in \mathbb{B} = \{1,2,3,4,5\}$ prior to the DHS survey interview date interacted with the household's farming status. All regressions separately control for household farming status and the various locust treatment bins. *Geographic Controls* include DHS survey location absolute centroid latitude, absolute centroid longitude, distance to the country's borderline, coastline river, capital city, largest settlement, catholic missions, protestant missions, railroad, and road. *Land Productivity Controls* include mean land suitability for agriculture, mean cropland coverage, mean pasture land, mean elevation, and std. dev. of elevation. *Socioeconomic Controls* include log mean lights intensity, log mean population size, and number of conflict events 1-12 months prior to the DHS survey interview date. *Weather Controls* include mean temperature, mean precipitation, mean potential evapotranspiration, drought intensity, and number of frost days 1-12 months prior to the DHS survey interview date. *DHS Individual Controls* include gender of household member ($1 = male$, $0 = female$), indicator variable equal to one if the household member is the son or daughter of the household head, and age fixed effects for each age category 3-24 of the household member. *DHS Household Controls* include the gender of the household head ($1 = male$, $0 = female$), indicator variables for each household size category ($1-9$ and > 10 household members), and indicator variables for the household head's highest attained educational level (i.e., primary, secondary, and higher education). *DHS Building Controls* include indicator variables if the household has access to electricity, piped water, and finished material floor building. *DHS Transportation Controls* include indicator variables if the household has a car or truck, a motorcycle or scooter, or a bike. *DHS Wealth Controls* include indicator variables of the household's wealth status (i.e., poor or middle). *DHS Media Controls* include indicator variables if the household has a radio or television. $Country \times Region \times Time\ FE$ are fixed effects of the calendar year and month of the country's region according to the DHS data. See the main text for additional details on data construction and sources. Clustered standard errors by DHS survey location level are shown in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table C2: Locust Ecology

	(1)	(2)	(3)	(4)	(5)
	Mean Number of Locust-Infested Months per Year				
Mean Annual Change of Temperature	0.391***	0.413***	0.398***	0.394***	0.417***
	(0.026)	(0.027)	(0.027)	(0.027)	(0.028)
Country FE	Yes	Yes	Yes	Yes	Yes
Terrain Characteristics	Yes	Yes	Yes	Yes	Yes
Geographic Characteristics	No	Yes	Yes	Yes	Yes
Drought Index	No	No	Yes	Yes	Yes
Land Suitability	No	No	No	Yes	Yes
Precipitation	No	No	No	No	Yes
Observations	40,993	40,993	40,993	40,993	40,993
Adjusted R^2	0.196	0.197	0.201	0.208	0.208

Notes: This table shows the estimates discussed in Section 5.4 in the paper. The dependent variable is the mean number of locust-affected months per year (counting both swarms and bands) in the time period from 1985 to 2020, based on a 0.25 DD rectangular grid. The main explanatory variable is the mean annual change of temperature in the same time period, measured in degree Celsius. *Terrain Characteristics* refers to the arithmetic mean and the standard deviations of terrain elevation. *Geographic Characteristics* refers to the natural logarithms of the grid cell centroid's absolute longitude and latitude. *Drought Index* refers to the average 12-month SPEI index over the time period 1985 to 2020 for the grid cell. *Land Suitability* refers to the average value of the grid cell's suitability for agriculture index. *Precipitation* is the average annual precipitation amount for the grid cell. Robust standard errors are reported in parentheses.

*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

Table C3: Locust Infestations and Years of Schooling – Baseline Results with DHS Controls, OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Current Years of Schooling						
$TM^{\overline{50}km}_{idct[f(1-24)]} \times Farmer_{hd}$	0.1077	-0.0675	-0.0643	-0.0644	-0.0965	-0.0882	0.0243
	(0.0836)	(0.0818)	(0.0810)	(0.0803)	(0.0745)	(0.0730)	(0.0419)
$TM^{\overline{50}km}_{idct[f(25-48)]} \times Farmer_{hd}$	-0.6662***	-0.1256**	-0.1742***	-0.1710***	-0.2209***	-0.2303***	-0.1985***
	(0.0735)	(0.0608)	(0.0592)	(0.0592)	(0.0583)	(0.0584)	(0.0356)
$TM^{\overline{50}km}_{idct[f(49-72)]} \times Farmer_{hd}$	-0.5133***	-0.6577***	-0.6166***	-0.6152***	-0.5657***	-0.5544***	-0.4015***
	(0.1031)	(0.1120)	(0.1098)	(0.1114)	(0.1097)	(0.1113)	(0.0614)
$TM^{\overline{50}km}_{idct[f(73-96)]} \times Farmer_{hd}$	-0.0227	-0.1684***	-0.1776***	-0.1752***	-0.1689***	-0.1629***	-0.1489***
	(0.0449)	(0.0418)	(0.0400)	(0.0400)	(0.0390)	(0.0388)	(0.0320)
$TM^{\overline{50}km}_{idct[f(97-120)]} \times Farmer_{hd}$	-0.6993***	-0.6140***	-0.6178***	-0.6180***	-0.6344***	-0.6293***	-0.4523***
	(0.0459)	(0.0389)	(0.0377)	(0.0378)	(0.0378)	(0.0376)	(0.0310)
Observations	2,210,388	2,210,388	2,210,388	2,210,388	2,210,388	2,210,388	2,210,388
Adjusted R^2	0.0333	0.142	0.154	0.155	0.159	0.160	0.624
Number of DHS Survey Locations	33498	33498	33498	33498	33498	33498	33498
Mean of Dep. Var.	3.094	3.094	3.094	3.094	3.094	3.094	3.094
Country×Region×Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Geographic Controls	No	No	Yes	Yes	Yes	Yes	Yes
Land Productivity Controls	No	No	No	Yes	Yes	Yes	Yes
Socioeconomic Controls	No	No	No	No	Yes	Yes	Yes
Weather Controls	No	No	No	No	No	Yes	Yes
DHS Individual Controls	No	No	No	No	No	No	Yes
DHS Household Controls	No	No	No	No	No	No	Yes
DHS Building Controls	No	No	No	No	No	No	Yes
DHS Transportation Controls	No	No	No	No	No	No	Yes
DHS Wealth Controls	No	No	No	No	No	No	Yes
DHS Media Controls	No	No	No	No	No	No	Yes

Notes: Data are from various DHS survey years in Africa. Observations are at the survey respondents level complemented with household, DHS survey location, and aggregated geo-spatial controls. The dependent variable is current years of schooling for individuals between the ages of 3 to 24 years. $TM^{\overline{50}km}_{idct(a)} \times Farmer_{hd}$ is a age-specific locust treatment indicator that counts the number of locust infested months during time bin $a \in \mathbb{B} = \{1,2,3,4,5\}$ prior to the DHS survey interview date interacted with the household's farming status. All regressions separately control for household farming status and the various locust treatment bins. *Geographic Controls* include DHS survey location absolute centroid latitude, absolute centroid longitude, distance to the country's borderline, coastline river, capital city, largest settlement, catholic missions, protestant missions, railroad, and road. *Land Productivity Controls* include mean land suitability for agriculture, mean cropland coverage, mean pasture land, mean elevation, and std. dev. of elevation. *Socioeconomic Controls* include log mean lights intensity, log mean population size, and number of conflict events 1-12 months prior to the DHS survey interview date. *Weather Controls* include mean temperature, mean precipitation, mean potential evapotranspiration, drought intensity, and number of frost days 1-12 months prior to the DHS survey interview date. *DHS Individual Controls* include gender of household member ($1 = male$, $0 = female$), indicator variable equal to one if the household member is the son or daughter of the household head, and age fixed effects for each age category 3-24 of the household member. *DHS Household Controls* include the gender of the household head ($1 = male$, $0 = female$), indicator variables for each household size category ($1-9$ and > 10 household members), and indicator variables for the household head's highest attained educational level (i.e., primary, secondary, and higher education). *DHS Building Controls* include indicator variables if the household has access to electricity, piped water, and finished material floor building. *DHS Transportation Controls* include indicator variables if the household has a car or truck, a motorcycle or scooter, or a bike. *DHS Wealth Controls* include indicator variables of the household's wealth status (i.e., poor or middle). *DHS Media Controls* include indicator variables if the household has a radio or television. $Country \times Region \times Time\ FE$ are fixed effects of the calendar year and month of the country's region according to the DHS data. Constant term included but not shown. See the main text for additional details on data construction and sources. Clustered standard errors by DHS survey location level are shown in parentheses.
*: Significant at the 10% level. **: Significant at the 5% level. ***: Significant at the 1% level.

D Figures

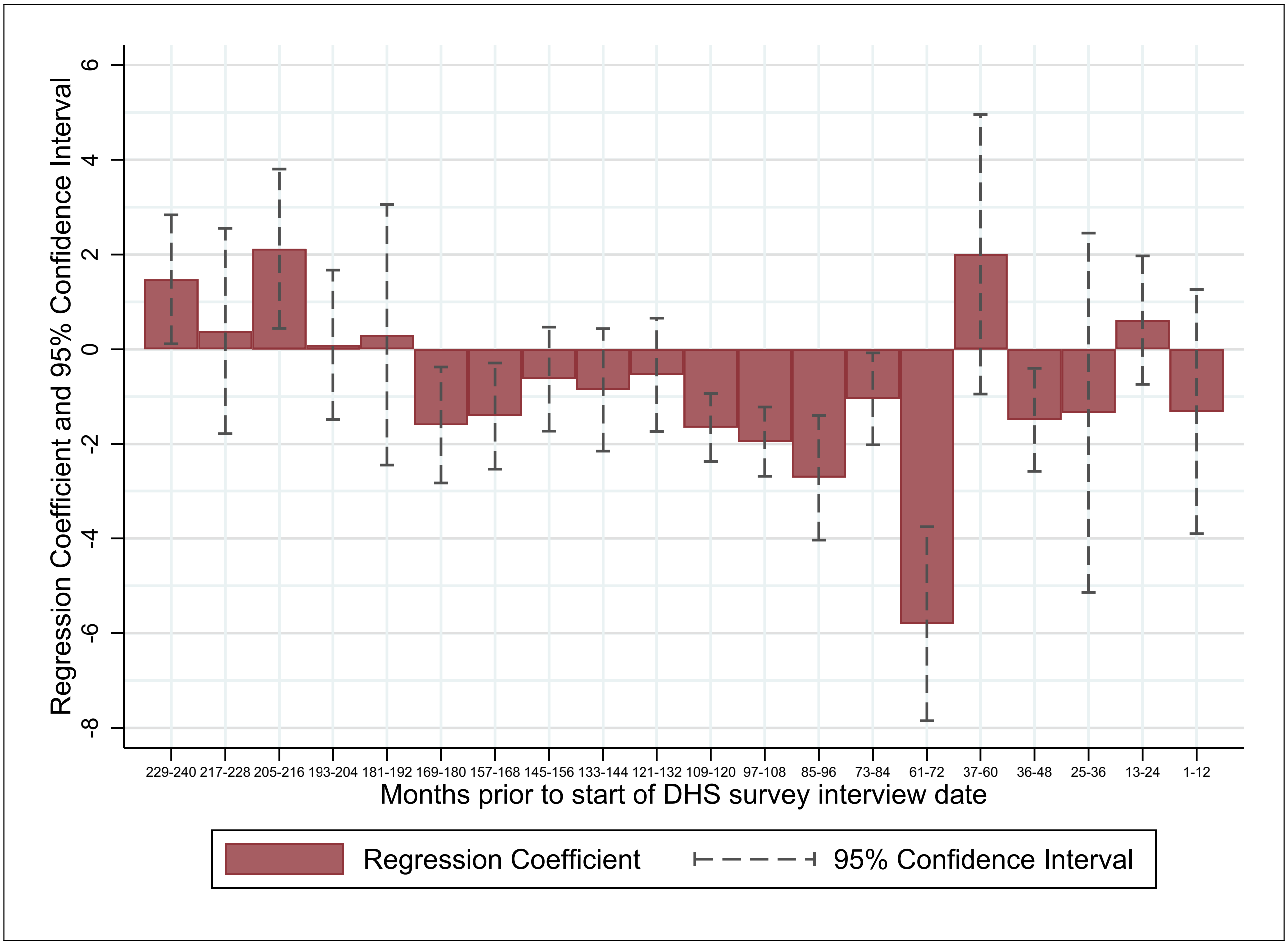


Figure D1: Dynamic Effects of Locust Exposure on School Enrollment Status

Notes: The figure presents estimated regression coefficients $\beta_3^{\tilde{a}}$ and the corresponding 95% confidence interval from estimating regression equation (4) on the sub lag components of the locust treatment control $TM_{idct(\tilde{a})}^{\overline{50km}}$ interacted with the household farming status variable $Farmer_{hd}$, where $\tilde{a} \in \tilde{\mathbb{B}} = \{1, 2, ..., 24\}$ is the time bin period (12 months interval) prior to the DHS survey interview date. The outcome variable is an indicator variable of being currently in school ($100 = yes$, $0 = no$) for individuals between ages 3-24 years. The regression include the full set of controls according to model specification (7) of Table 3. See the main text for additional details on data construction, sources, and estimation methodology.

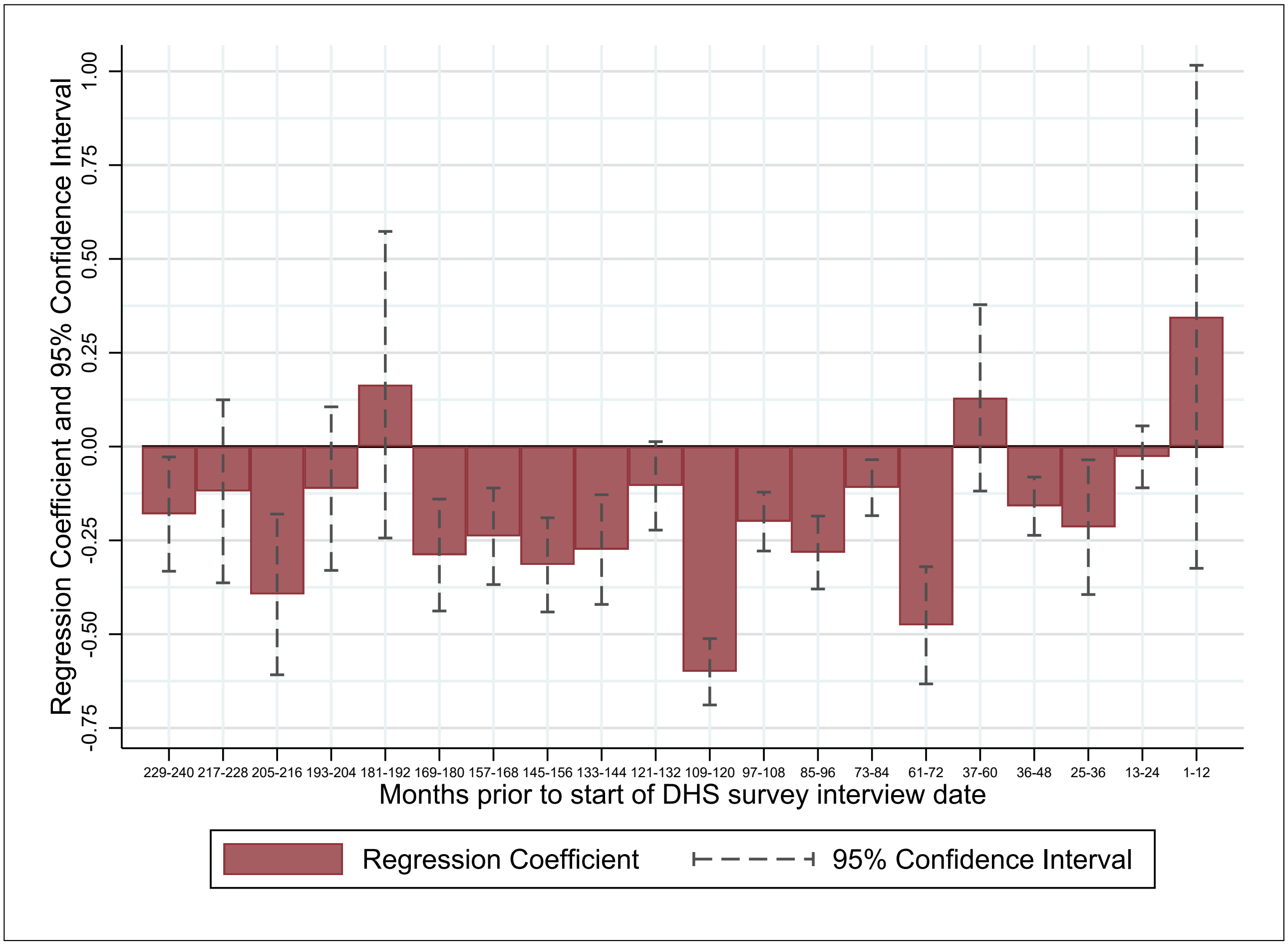
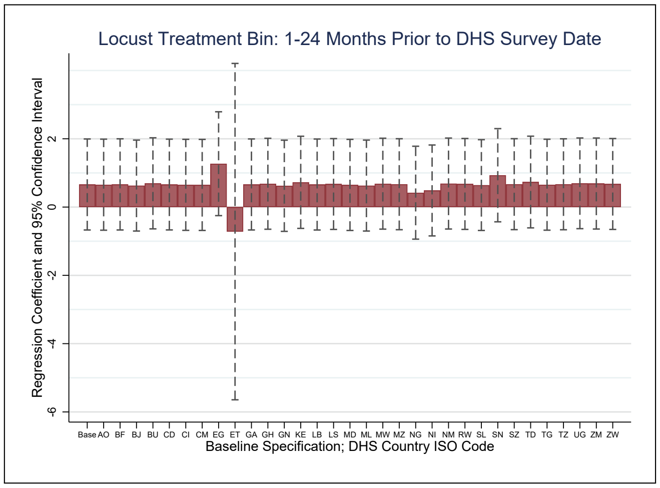
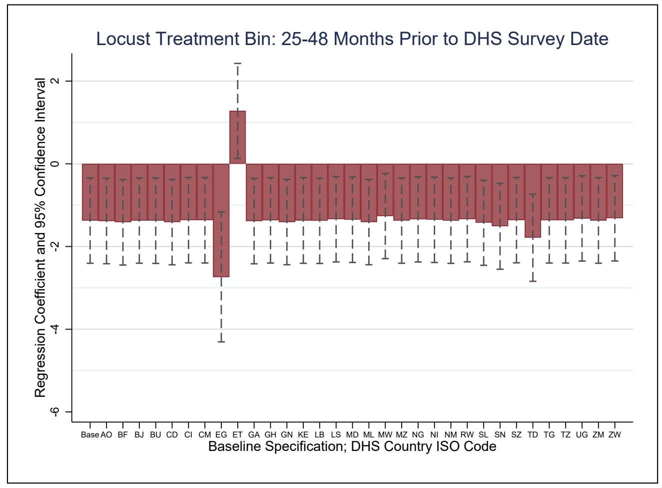


Figure D2: Dependent Variable: Years of Schooling

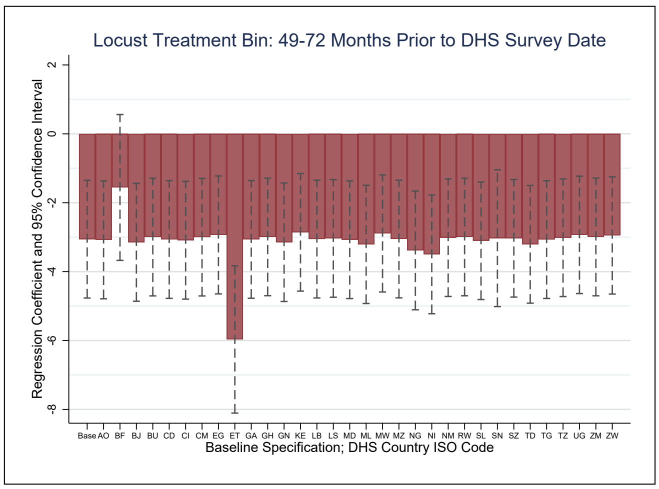
Notes: The figure presents estimated regression coefficients $\beta_3^{\tilde{a}}$ and the corresponding 95% confidence interval from estimating regression equation (4) on the sub lag components of the locust treatment control $TM_{idct(\tilde{a})}^{\overline{50}km}$ interacted with the household farming status variable $Farmer_{hd}$, where $\tilde{a} \in \tilde{\mathbb{B}} = \{1, 2, ..., 24\}$ is the time period prior (12 months interval) to the DHS survey interview date. The outcome variable is accumulated years of schooling for individuals between ages 3-24 years. The regression includes a full set of controls according to model specification (7) of Table 3. See the main text for additional details on data construction, sources, and estimation methodology.



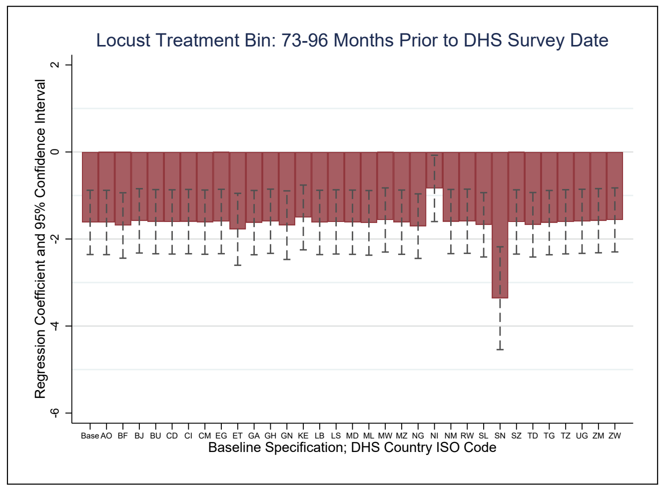
(a) Locust Treatment Bin 1



(b) Locust Treatment Bin 2

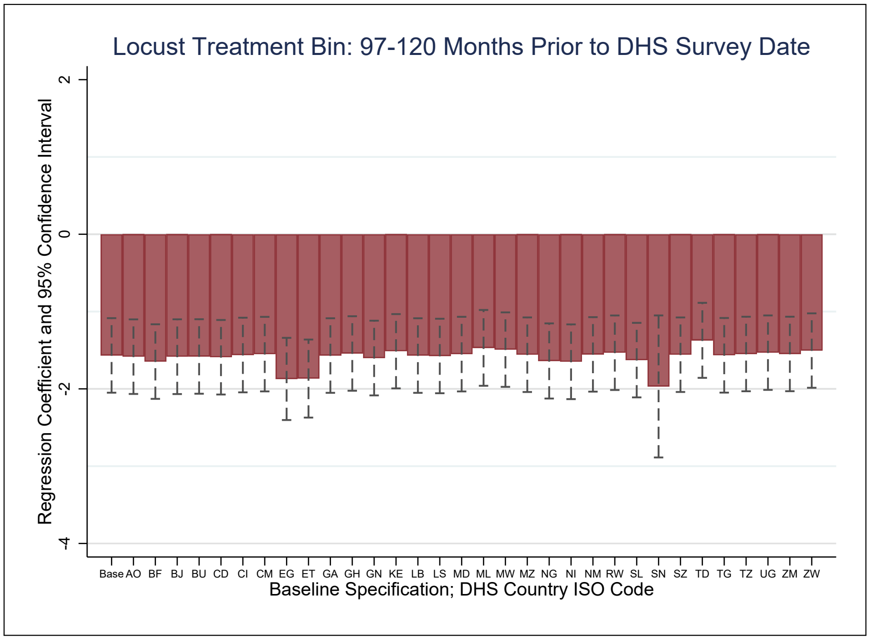


(c) Locust Treatment Bin 3



(d) Locust Treatment Bin 4

Figure D3: Robustness to Leave-One-Country-Out Specification



(e) Locust Treatment Bin 5

Figure D3: Robustness to Leave-One-Country-Out Specification

Notes: The figure shows the robustness of the main results from estimating regression equation (4) by subsequently excluding observations from each country from the baseline sample. The vertical axis presents estimated regression coefficients β_3^a and the corresponding 95% confidence interval on the different time lag bins $a \in \mathbb{B} = \{1,2,3,4,5\}$ of the locust treatment control $TM_{idct(a)}^{\bar{b}km}$ interacted with the household farming status variable $Farmer_{hd}$. The outcome variable is an indicator variable of being currently in school ($100 = yes$, $0 = no$) for individuals between ages 3-24 years. The horizontal axis provides the DHS country 2-letter ISO code of the excluded country observations from the baseline sample. The regressions include the full set of controls according to model specification (7) of Table 3. See the main text for additional details on data construction, sources, and estimation methodology.

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