The disease environment, schooling, and development outcomes: Evidence from Ethiopia*

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Abstract

The disease environment in general, and malaria in particular, could help explain underdevelopment in many regions of the world, especially in Africa. Using data from Ethiopia, this paper provides evidence that *local* malaria risk is associated with worse local development outcomes. By combining information from a large-scale Ethiopian household survey with satellite-derived topographical information on 1,000 villages, the paper shows that self-reported malaria incidence is highly correlated with village elevation, slope, and the interaction between elevation and slope. That is because malaria is sensitive to elevation differences in flatlands, where the habitat is suitable for mosquito breeding, and is less sensitive to elevation in steeper lands. Using topography as a predictor of the disease environment, I find that education levels are worse in areas with more adverse disease environments. I find weak or no conclusive evidence that other village outcomes including wealth and food insecurity are related to malaria risk.

JEL Classification: O15, I15, I25

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1 Introduction

Debates over the lack of development and growth in sub-Saharan Africa often boil down to weighing the merits of two contrasting camps. The "environment" camp argues that disease

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and hostile environments are an impediment to human and physical capital investments. Proponents have used results from cross-country growth regressions augmented with data on malaria incidence to argue that tropical diseases like malaria keep mortality high, reduce human capital, and pose a constraint to economic growth (Gallup and Sachs, 2001). On the other camp, Acemoglu, Johnson and Robinson (2001) have famously proclaimed the primacy of institutions over Nature as the reason for underdevelopment: African nations never developed institutions that were conducive to social and economic growth. Accordingly, the fact that malaria enters negatively into cross-country growth regressions has little to do with the direct effect of that disease today. Rather, it can be explained by its impact hundreds of years ago, when it caused high mortality among colonists that impeded the establishment of states with European-minded rule of law. The debate is important. If the greatest impediment to development is the disease environment, then a first order priority for African nations is to eradicate or control as many tropical diseases as possible. If disease is not a root cause, then development efforts should focus in other areas.

This paper provides new evidence on the relevance of the disease environment in Ethiopia along several dimensions of development–including schooling, wealth, and exposure to shocks– while keeping "institutional quality" constant. Ethiopia is a particularly suitable country to examine because of the significant and largely predetermined differences in disease environment, and even villages in close proximity to one another can have starkly different health risk profiles. In particular, Ethiopian villages vary considerably in their exposure to malaria, a widespread tropical disease that is a leading cause of morbidity and mortality in sub-Saharan Africa and elsewhere. The main explanation for this is the complex topography of this mountainous country, and the sensitivity of malaria transmission to local differences in elevation and slope. Here, I use differences in the *interaction* between elevation and slope as exogenous shifters of a self-reported measure of malaria incidence, which can be used to obtain a measure of the correlation of malaria exposure to schooling and other development outcomes.

I study the correlation between local malaria endemicity and local development outcomes by matching a large-scale household survey with satellite-derived weather and topographic maps, which provided geographical and meteorological information on each village and include elevation, temperature, rainfall levels, and slope. The survey used, the Welfare Monitoring Survey (WMS) of 2004, surveyed approximately 1,000 villages and provides precise measures of schooling, self reported disease, and other household-level outcomes for a random sample of residents. Importantly, the survey was carried out before large-scale malaria interventions took place, starting in 2007. With this data, I find that the *interaction* between elevation and slope captures malaria rates quite well. That is because malaria is sensitive to elevation differences in places (flatlands) where the habitat is suitable for mosquito breeding, and is not sensitive to elevation in unsuitable areas (steep lands). In addition, the variation in topographic characteristics is large enough that it is possible to estimate differences in malaria incidence across villages located within the same province (*wareda*), the smallest administrative unit in Ethiopia after the village. Since most administrative units, local markets, and school administration are centralized at the provincial level, the within-estimator eliminates a large source of heterogeneity in health, education, and other unobserved variation in weather, disease patterns, agricultural practices, and cultural traditions. Using topographical features as instruments for the variation in malaria, I find evidence that village outcomes are correlated with malaria endemicity. In particular, moving from a village with no malaria to one with average malaria (as measured by the WMS) is associated with 0.14 fewer years of schooling for children and 0.35 for adults. On the other hand, I find weaker evidence that other village outcomes –such as food insecurity or wealth accumulation–are related to malaria endemicity.

It is important to note that a causal interpretation of my findings requires topography to be uncorrelated with other possible drivers of local development. It is likely that elevation and slope are correlated with many factors other than disease, including agricultural production, households wealth, and the returns from education. It is less clear whether the *interaction* between elevation and slope should be correlated with those same factors, after controlling for the direct effect. To gain a better sense of which factors might be important confounders, I also explicitly study the relationship between topography and a number of village variables, including exposure to (non-health) shocks, distance to facilities like schools, and measures of population pressure. I find some evidence that some factors–like droughts and proxies for population pressure–also vary with topography. To the extent that these confounding factors are observable and can be controlled for, I find that they have a negligible impact on my estimates.

Several papers study the effect of malaria on schooling and economic development, but for the most part these papers do not use African data. Barreca (2010) used variation in rainfall and temperature in the 1920s American South and estimates that a standard deviation increase in exposure to in-utero and postnatal malaria reduced education by 0.23 years. Bleakley (2010) and Lucas (2010) use the timing of malaria eradication in the US, Latin America and Sri Lanka to estimate the effect of malaria on education and earnings, finding that education rates increased post eradication. Using a similar methodology, Percoco (2011) finds similar results for Italy, while Cutler et al (2010) do not find improvements in schooling but some modest increases in adult earnings. It is important to highlight important differences in the desease environment between African and the rest of the world. Malaria eradication was attempted but not successful anywhere in Africa (Webb, 2009). The reason for this is that the disease ecology/environment in Africa is unusually complex relative to the other continents, making eradication difficult and ensuring that the effects of the disease are more pronounced than elsewhere. Successful eradication in Africa would require dealing with all four types of malaria parasite (*P. Falciparum, Ovalae, Vivax, Malariae*) and dozens of mosquito species, some of which are considered extraordinarily effective in transmitting disease and avoiding the standard methods of mosquito control interventions (D'Antonio and Spielman, 2001). By comparison, in places where large-scale, broadly successful eradication or control took place—Southern Europe, the American South, and parts of Latin America—malaria was less entrenched and the mosquito vectors easier to be dispensed with. These differences in environment between eradication countries and countries with heavy disease burden suggest the need to be cautious in applying estimates from one to the other. In addition, the problem of malaria is perceived to be worst on that continent, primarily due to the incidence of *P. Falciparum*, a vector responsible for most malaria mortality. In fact, an estimated 90% of malaria induced child deaths occur in Africa (Cook and Zumla, 2008).

The rest of the paper is structured as follows: the next section provides background information on Ethiopia and malaria. Section 3 presents the data. Section 4 discusses the methodology. Section 5 include the main results from the paper. The conclusion follows.

2 Background

2.1 Malaria

Malaria affects approximately 250 million people and is responsible for one million deaths annually (WHO, 2009). This disease is transmitted to humans through bites of female *anophelae* mosquitoes. Once infected, a person can develop chills, very high fevers, anemia, and—especially in children less than 5 years of age—brain damage, coma, and death. The seriousness of symptoms depends, to a great extent, on the degree of parasitaemia, itself a function of the number of infected bites suffered by the patient (the inoculation rate). In general, the higher the inoculation rate, the higher the chance of severe symptoms or permanent damage.

In Ethiopia, the estimated incidence rate for malaria (i.e., the estimated probability of contracting the disease in a year) was 15% in 2005, which is somewhat low relative to the rest of sub-Saharan Africa (where the average incidence rate is 0.33), but higher than any other country outside of sub-Saharan Africa bar Panama, Laos, Myanmar, and the Solomon Islands (Korenromp, 2005). Despite the somewhat low incidence rate, this country is an appealing place to do a study on malaria for at least two reasons. First, malaria is still a very important public health problem: Ethiopia is thought to experience some 10 million cases per year, the fourth highest case number in sub-Saharan Africa (behind Nigeria, the DRC, Tanzania, and Uganda [Korenromp, 2005]). According to an Ethiopian report, clinical malaria accounts for

10 - 40% of all outpatient consultations, 13 - 26% of inpatient admissions at various health facilities, and is responsible for 15-17% of case fatalities in health facilities (WHO, 2006).

A second reason for considering malaria in Ethiopia is that, unlike most other African countries, there is extensive local variation in malaria incidence. Figure 1 and 2 make this clear. The figures show the predicted malaria incidence across the continent, according to the MARA model (MARA, 2011).[1] For most countries, malaria incidence has extremely high spatial autocorrelation. Ethiopia, on the other hand, has a very low degree of spatial autocorrelation; malaria in Ethiopia is a localized disease. Studies indicate the presence of spatial autocorrelation in malaria rates for villages located within 5 to 10 kilometers, dropping rapidly after that (Yeshiwondim et al, 2009). This feature permits the estimation of the impact of malaria incidence by comparing villages in close proximity to one another.

2.2 Transmission: slope and temperature

Malaria transmission is affected by land slope and temperature. The effect of temperature is well recognized in the malaria literature: increases in temperature increase the survival rate of mosquito larvae and reduce the length of sporogony—the time it takes for a mosquito which has ingested infected blood to be able to transmit the disease (Cook and Zumla, 2008), thus speeding up transmission. Below a certain temperature threshold (corresponding to approximately 18 degrees Celsius), sporogony is sufficiently slow that it cannot be completed before the mosquito dies, making malaria transmission impossible (Craig, Snow and le Sueur, 1999).

In Ethiopia, air temperature is largely determined by elevation. Figure 4 shows the relationship between elevation and the average daily temperature in the warmest month for Ethiopia. Above 2,500 meters of elevation, temperatures are consistently below the no-malaria threshold, making villages located there malaria-free.[2]

[1] The Mapping the Malaria Risk in Africa collaboration integrates rainfall and temperature information to generate a model of malaria prevalence for sub-Saharan Africa.

[2] In this paper, I focus on elevation as opposed to temperature because the entomological literature is unclear about how to take into consideration daily and seasonal variations in temperature. Nonetheless, given the strong linear relationship between the two measures, all results in this paper are very similar when replacing elevation

A second determinant of malaria incidence is the presence of mosquito breeding grounds. Anopheles mosquito larvae need stagnant water pools to reproduce, and environments with scarcity of bodies of water sustain smaller mosquito populations. On average, villages that are very sloped are less likely to have stagnant water pools, as rainfall converges to river systems downstream. In addition, larvae developing in water pools in sloped areas are more likely to be washed away during downpours, and might be more likely to be targeted and eliminated by drainage activities carried out by local villagers. Thus, sloped areas make for poor mosquito breeding ground, reducing the threat of malaria transmission, especially in the higher elevation areas that are the focus of the present study (Balls et al, 2004).

Since villages that have a high slope gradient are inhospitable to mosquitoes, the incidence rate among villages located in steeplands is low, regardless whether they are located in high elevation or low elevation areas. On the other hand, villages located in flatlands are more likely to have a suitable environment for mosquito breeding; with mosquito populations not being a limiting factor of local disease transmission, elevation is likely to play an important role in malaria transmission, with high elevation villages having significantly lower incidence rates than low elevation villages. In other words, the *sensitivity* of malaria incidence in regards to elevation should increase the flatter the local topography.

To be sure, malaria is not the only vector borne tropical disease that might be influenced by temperature and terrain. Other candidate diseases, however, follow different patterns of transmission. Dengue fever (transmitted by mosquitoes) is generally concentrated in urban areas and is found sporadically in Ethiopia (Aseffa, 1993); Yellow fever and Chikungunya (also transmitted by mosquitoes) are rare in the country;[3] Sleeping sickness (transmitted by tze-tze flies) is also found sporadically (Fevre et al, 2006) as is Rift Valley fever (which, in any case, has severe morbidity and mortality rates in less than 1% of patients [WHO, 2010a]). Ethiopia is considered at a high risk of meningitis epidemics (Cuevas et al, 2007), and while there is some

with average daily temperature, with results available upon request.

[3]Aseffa [1993] reports no cases in Ethiopia from 1966, and the WHO in 1995 reported no cases between 2000 and 2004. In 2004, there were a total of 128 suspected yellow fever cases in sub-Saharan Africa.

association between environmental factors (rainfall, forest cover, dust levels, human population density) and the spread of the disease, the relationship between meningits and either elevation or slope is not understood.[4] Other diseases, like diarrheal diseases or influenza, might be affected by land slope or temperature, but they are unlikely to be affected by the interaction of the two.

3 Data

The Welfare Monitoring Survey (WMS) was conducted by the Ethiopian Statistical Agency between June 24 and July 3 of 2004, and it involved over 2,000 villages across all states in the Ethiopian Federation. It covers basic individual and household characteristics, as well as access to several services. Crucially, it includes information on both schooling and individual level health conditions (including self-reported malaria spells) in the preceding two months. These health outcomes refer to the months May and June, corresponding to the end of the short rains (known as the "*belg*") and of the short malaria season (which generally runs from mid-March to June).[5] In particular, for each member of the household, the survey asks whether the individual faced a health problem in the prior two months and, if so, what was the reason for this sickness. The questionnaire provides six different reasons, including malaria. Using this information, I constructed a measure of self-reported recent malaria incidence at a village level as the fraction of the surveyed population who was reported as suffering from malaria.[6] Since this measure of malaria incidence comes from self-reported diagnoses, they might well be wrong: those reporting malaria might simply be suffering from fevers or pain from other types of infections or diseases. In addition, the self-reported nature of the malaria incidence measure

[4] Meningococcal bacteria is spread person to person through cough droplets, so there is not a direct connection with topographical factors. The most recent epidemic prior to the study period was in 2001-2002, where a total of 1,332 cases and 85 fatalities were identified (WHO, 2002).

[5] The peak malaria season in Ethiopia is September to November, after the long rains (*meher*). The timing of rains varies from region to region.

[6] Malaria in the highlands fluctuates from year to year and seasonally. Fortunately, the survey was taken between June 24 and July 3, a period that generally follows the peak of the minor transmission season (March-June). Thus the survey covers a period of malaria transmission.

creates a series of problems when estimating the relationship between malaria and important outcomes. For instance, more informed households (which presumably have a higher demand for education) might also be more likely to report disease spells. And even if malaria incidence were measured with no bias or error, villages with higher investments in education might also value higher investments in malaria prevention and lower malaria rates, thus biasing estimates upward.[7]

Since it is unlikely that measurement error or reverse causality are as problematic if village *topography* is used in place of self reported village malaria, the WMS was integrated with measures of village topography derived from the use of two additional datasets. The first database is an electronic map developed by the Ethiopian Development Research Institute (EDRI), in collaboration with the International Food Programme Research Institute (IFPRI). Researchers at these institutes transferred paper maps of all Ethiopian administrative units into digital form. These digital maps spatially divide the country into its administrative units, from largest (states) to smallest (villages). Using the EDRI/IFPRI electronic maps, I matched the names of the villages in the electronic map with the names of the WMS villages for the regions of Ahmara, Oromia and SNNP (see figure 6). I was unable to match a number of villages within these regions that were fully mapped, mostly due to discrepancies in the name in the WMS and in the EDRI/IFPRI maps. In total, around 35% of villages in the three regions were dropped. Unfortunately, it appears that dropped villages are different from mapped villages along several different dimensions. They appear more rural and a little poorer and less educated. Thus, the sample used here is not representative of Ethiopian villages.

Elevation, temperature, rainfall and slope for the entire country of Ethiopia come from remote sensing data collected by NASA satellites and elaborated by scientists at the Livermore National Laboratory in California. This data shows, for any coordinate point in Ethiopia, its elevation, slope, average rainfall, and minimum, maximum and average daily temperatures for each month of the year. I transferred the remote sensing data to the EDRI/IFPRI map by

[7] At the time of the survey, mosquito nets were quite rare in rural Ethiopia. However, malaria incidence is sensitive to environmental management, which might occur in wealthier villages.

averaging elevation and temperature over the entire surface of each village.

Table 1 provides summary statistics of the study villages, and separately for villages located below the 2,500 meter threshold. 84% of villages are located between 600 and 2,500 meters above sea level, with the remainder being high altitude villages located up to 3,500 meters in elevation. Average village slope is 6.7%, meaning that there is an average 6.7 meter gain per 100 meters.

Around a quarter of individuals were sick in the prior two months. A quarter of sick respondents reported suffering from malaria, half did not report a specific disease, and the rest were evenly divided among other health problems (diarrhea, tuberculosis, ear, nose and throat problems, other injuries). As one would expect from the discussion, the rate of reported sickness is significantly lower in high altitude villages: only 20% of individuals there reported some sickness, and essentially none reported suffering from malaria. The dependent variables of the paper (years of schooling for children aged between 7 and 19 and adults) are presented next. At the time of the survey, children who were currently in school were in between grades due to the summer break. Since many are still enrolled, average schooling for children is somewhat different from adults, who have largely completed formal education. On average, both the children sample and the adult sample report having one year of schooling.

The rest of the table describes some of the key household characteristics found in the sample. Since I exclude urban and peri-urban household and focus entirely on rural villages[8], the vast majority (92%) of households are farming families, with 4% declaring having no land ownership. The survey includes information on a number of assets, which I summarize into a unique vector of wealth.[9] The households interviewed are generally quite poor, reporting generally few assets. 23% of households are female headed. Ethiopians are livestock-rich (almost five units of either sheep, goats, donkeys or cows per household), and most households own at least one ox, which is used to till the land and is a significant determinant of productivity. I also

[8] I was given access to rural data only.

[9] Specifically, the index is the first factor obtained from the principal component analysis of the assets available in the questionnaire.

report exposure of households to shocks, as measured by the number of times the household suffered a given problem in the prior 5 years. Droughts and livestock losses are frequently reported, as are deaths in the family (an average of 0.28 deaths in the past 5 years). Finally, the data includes information on distance of the household to several types of facilities, including schools and clinics. Primary schools are relatively close, on average 45 minutes on foot. Health facilities (as well as secondary schools, hospitals, and other services reported in the survey but not on this table) are far, averaging well over 2 hours walking. In general, such services are often located in the district town, a few miles away from most villages. Finally, there are some differences by elevation: in particular, high elevation villages generally report fewer shocks, and have higher amounts of livestock.

4 Methodology

The objective of this paper is to exploit the correlation between malaria incidence and topography to explore the correlates between local malaria incidence and local development outcomes. The strategy is to first demonstrate how self reported malaria is explained by village elevation, village slope, and the *interaction* between the two. We then use an instrumental variable approach to explore the correlation between malaria and development outcomes, including schooling, asset accumulation, and labor supply. Formally, I model village malaria incidence in the following regression:

$$malaria_v = \alpha_v + \beta_0 Elevation_v + \sum_{j=2,\dots,5} \left[\beta_1^j + \beta_2^j \times Elevation_v\right] \times Slope_v^j + \eta X_v + \epsilon_v. \quad (1)$$

$Elevation_v$ indicates village height (in hundreds of meters), $Slope_v^j$ is a dummy indicating villages in the j-th quintile of slope,[10] α_v is a province fixed effect, and X_v is a set of village-level controls. In addition to malaria, I use the same regressors to show existing correlations

[10] The first quintile of slope goes from 0 to 2.5%; the second quintile from 2.5 to 4.5%; the third from4.5% to 6.8%; the fourth from 6.8% to 10.2%, and the last from10.2 to 26%.

between topography and other health outcomes, including other sickness and mortality. β_0 estimates the correlation between elevation and the outcome variable in areas that are very flat; β_1 shows the effect of slope; and β_2 measures the effect of the interaction between elevation and slope. Alternatively, the effect $\beta_2^j - \beta_0$ measures the correlation between elevation and the health outcome variable for those villages located in slope quintile j. Based on this model, we expect malaria incidence to be negatively related to elevation and slope (i.e., β_0 and $\beta_1^j < 0$), but positively related to the interaction: the steeper the area, the less sensitive malaria incidence is to increases in elevation. Thus, we expect $\beta_2^{j+1} > \beta_2^j > 0$.

The above analysis and interpretation is applied to a subsample comprising of villages with some positive risk to malaria–that is, places located below 2,500 meters. As an additional robustness test, I will also model malaria incidence with an agumented regression that includes the full sample–thus including villages above 2,500 meters. A dummy variable *above* $2,500m$ is added and fully interacted with both elevation and slope quintiles such that each β_0, β_1^j and β_2^j is identified separately for villages located above and below the 2,500 meter threshold.

Having used topographical features to generate a prediction of the local malaria environment, I use predicted malaria incidence in a second stage of the regression:

$$y_v = \alpha_v + \gamma_1 \widehat{malaria}_v + \delta_0 Elevation_v + \sum_{j=2,\ldots,5} \delta_1^j Slope_v^j + \xi X_v + \epsilon_v, \qquad (2)$$

where y_v is an outcome of interest in village v average education and schooling outcomes for adults and children, average asset ownership, and exposure to shocks. Note that the second stage includes elevation and slope quintiles, but excludes the interaction term. To the extent that *interaction* between elevation and slope do not directly affect the outcome variable–that is, the exclusion restriction holds–the coefficient γ_1 identifies the causal effect of malaria on outcome y. Since the exclusion restriction may not hold due to the presence of other omitted variables, the preferred interpretation for γ_1 is of a correlation between malaria and development outcomes that is free of measurement error and endogeneity.

All specifications include province fixed effects α_v, which absorb the unobserved variation within provinces, and a set of control variables X_v. In regressions involving children's outcomes, controls included are average rainfall and village averages of child age, education of household heads, education of spouses, ownership of oxen and livestock, household asset ownership, distance to primary schools and health centers, the fraction of households with a female household head, plot size of agricultural households, and drought prevalence. The control set X_v for regressions on adult schooling include only cohort age, distance to facilities, land sizes and drought prevalence.[11] Finally, since sickness and education are likely correlated at the village and province level, I obtain conservative standard errors by running regressions at the village level, and by clustering errors at the province level. Since the WMS carried out the same number of interviews in each village, the results are not weighted.

5 Local conditions and topography

5.1 The disease environment

To show how topography influences health outcomes through malaria, figure 4 shows a local linear estimate of the relationship between self reported malaria incidence (as described in section 3) and village elevation. As altitudes increase, the proportion of the villagers reporting having suffered from malaria decreases. The proportion of villages suffering from malaria remains flat and close to zero for elevations above 2,500 meters, as expected. The relationship between slope and elevation is shown in figure 5, which reports the local linear estimate of the relationship between self reported malaria and land slope. Malaria rates are high in flatlands, with the estimated rate falling monotonically at higher slopes.

To formalize the results from the two figures, table 2 provides an initial overview of the relationship between health and topography in Ethiopia through a regression of disease

[11] Results presented here are robust to changes in the controls, including the addition of distances to other facilities and services and average exposure to shocks. For simplicity, first stage results (tables 2, 3 and 4) employ the child regression controls. Using adult controls does not change the results.

incidence on village elevation, slope, and a full set of covariates. The odd columns of the table report coefficient estimates for villages located below 2,500 meters of elevation. Even columns also include villages above the threshold; the column reports the main estimated effect for villages below the threshold as well as the estimate from an "above 2,500 meters" dummy interacted with elevation.

Columns 1 and 2 consider overall health incidents. It confirms that higher elevation villages are healthier: on average, each 100 meters of elevation gain reduces sickness by 0.8 percentage points, or approximately 3.3% of the average level of village sickness. Moreover, this correlation disappears above the 2,500 meter line (column 2), something that would be expected if the correlation is driven by malaria. Land slope is negatively correlated with sickness, but the coefficient is insignificant. In columns 3 and 4, I consider self-reported malaria. The coefficient on altitude indicates that just 100 meters gain in elevation is sufficient to reduce malaria by 0.6 percentage points, which is 10.5% of mean malaria—a very high rate. Slope is now strongly significant, indicating that more sloped villages have lower reporting of malaria. One way to consider the magnitude of the effect is to consider that moving from an area with zero slope to one with average slope (6.7%) reduces malaria incidence by 2 percentage points– over a third of mean malaria. Above 2,500 meters (column 4) the negative correlation between malaria and elevation disappears. Columns 5 and 6 show the relationship between other types of sickness (all causes excluding malaria) and elevation and slope. The estimated effects are small and statistically insignificant. This assures us that the linkage between health and elevation is driven by malaria. Finally, the last two columns of the table shows results for the measure of mortality present in the survey (number of deaths in the household in the past 5 years). This measure is noisy, as it includes all mortality for all age groups and for any reason. While the estimates move in the same direction as those found in the malaria regressions, the estimated coefficients are all insignificant.

Estimates of equation (1) are presented in table 3. The table shows whether the *interaction* between elevation and slope can be used to predict adverse health reporting. Column

1 shows that this is not the case for overall sickness. While sickness decreases with elevation, this relationship is found across slopes. When focusing on malaria only (column 2), I find that elevation predicts malaria in villages located in the bottom four quintiles of land slope—but not in the steepest villages, which have low incidence rates everywhere. The point estimates suggest that the impact of elevation on malaria declines the steeper the village. Moreover, the interaction coefficients are jointly significant: the p-value on the F-statistic of joint significance is 0.07.[12] Column 3 looks at all-cause sickness excluding malaria. I find that sickness and elevation are not related in flatlands, but overall other cause health problems decline at higher slopes. Taken individually, diseases such as diarrhea, tuberculosis, ear, nose and throat problems, and other types of injuries are sometimes correlated with elevation at higher slopes only (not shown). Thus, the pattern of high correlation with elevation in flatlands is specific to malaria. Finally, mortality (column 4) again follows a clear pattern consistent with malaria, but the coefficients are not statistically significant.

5.2 Other factors and topography

A key issue is that topography could be correlated with a host of other factors affecting local development other than malaria. For instance, elevation alone could affect farm productivity and exposure to weather shocks. Higher elevation villages might also have closer access to schools, services, or labor markets where returns to education are higher. Migratory patterns might also differ across topographical areas, for various reasons. Finally, the highlands in Ethiopia are known to be densely populated, and this could affect the level of wealth or schooling in the community. To the extent that these factors are correlated with the *interaction* between elevation and slope, they represent alternative pathways through which topography shapes local development.

Table 4 explores a number of these potential correlates. First, column 1 through 4 report

[12]Since the malaria measurement was not taken at the peak of the malaria season, the instrument set is somewhat weak; to improve the robustness I will employ the expanded set of instruments. See appendix A for the first stage results.

estimates from the regression (1) on a number of different types of agricultural shocks–namely, the number of instances the household suffered floods, droughts, livestock losses, a price shock or some other (non-health) shock in the prior 5 years. Droughts are indeed correlated with the interaction between slope and elevation, with the incidence of droughts declining with elevation in flatlands but not in steeplands. Shocks to livestock are significantly correlated with elevation in quintile 2 and 4 of slope, while floods and other shocks cannot be explained by topographic factors. Next, I make use of household-specific distances to schools and clinics to control whether location to public services differs by elevation and slope (columns 5 and 6).[13] School distance does not decrease with elevation in low sloped areas, but it does for highly sloped areas–the opposite pattern observed for disease. Third, we would like to check how topography correlates with migration and population pressure. Unfortunately, the data does not include this information. As a partial and admittedly unsatisfying check, I consider in column 6 the average length of land tenure (where villages at the receiving end of *recent* migratory flows should have lower tenure length); I find that land tenure does not correlate with topography. Forth, I study two important correlates of population density–the fraction of households that are landless in column 7 and the average size of land holdings in column 8. Both measures seem to vary somewhat with topography; in particular, land sizes decrease with elevation, especially in the steepest areas.

Overall, the table demonstrates the presence of some topography covariates that may be important co-determinants of development outcomes. Most of the positive evidence in the table points to an elevation gradient in steeplands; much less so for flatlands. In all regressions, I control for land sizes and droughts. The estimates are not sensitive to their inclusion.

[13]School and clinic distance is a convenient proxy to distance to other services, since distances to other services (like markets, roads, sources of farm goods, and so on) behave in a similar pattern.

6 Malaria environment and development outcomes

6.1 Schooling

6.1.1 Reduced form results

Having established that recently reported malaria is strongly correlated to topography in a specific way, I now show how topography correlates with other development outcomes in a similar way by reporting reduced form results from a regression of topography on schooling. In table 5, I regress the average years of schooling for children (age 7-19) and adults (age 20+) on elevation, slope, and covariates, first focusing on elevations below the 2,500 meter threshold (columns 1 and 2) and then on all villages (columns 3 and 4).[14] Average schooling increases with elevation for both adults and children. Conversely, the higher the slope of the village, the lower the educational attainment. Moreover, when slope dummies are interacted with elevation (column 5 and 6), regressions show that there are gains in education from elevation in flat areas, but the higher the slope, the lower the gain: 100 meters of elevation gain correspond to an additional 0.095 years of schooling for children and 0.078 years for adults for those living in flat areas. The gain in schooling declines as slope increases, and there are no gains for those living in the steepest areas. This pattern is consistent with malaria lowering educational attainment.[15]

6.1.2 Instrumental variable results

I turn to instrumental variable estimates in table 6, panels A (children) and B (adults). Here, I use village topographical characteristics as instruments for malaria incidence, and look directly

[14]Results are robust to changes in the covariates. While coefficients on covariates are not shown, they move in the expected direction: parental wealth and education increase childrens schooling and distance to schools decreases it. Livestock ownership is associated with more schooling, suggesting that the income effect from livestock trump substitution effects arising from the fact that animal husbandry is an important labor activity of Ethiopian children.

[15]As a further check, regressions on the entire sample with a triple interaction term between elevation, slope quintiles and a dummy for above 2,500 meters lead to very similar results on the interaction terms: significant and declining interaction terms for those below the threshold, insignificant if above the threshold.

at the impact of recent self-reported village malaria on average years of schooling for children and adults, with results disaggregated by gender. In the first column, I report OLS results. In column 2, I use 2SLS with elevation as an instrument. In column 3 I report my preferred specification, which controls for elevation and slope quintiles and uses the interaction between elevation and slope as instruments. In column 4 I run a robustness test which includes all observations from all elevations, where the instrument set includes the interaction between quintiles of slope, elevation, and whether a village is located above 2,500 meters. This specification allows me to reduce a weak instrument problem with the main specification.[16] I also report IV estimates from a limited maximum likelihood estimation (LIML), which reduces any biases originating from having many instruments or weak instruments. The instruments for column 3 and 4 are weak; using LIML improves the situation: The Kleibergen-Paap Wald rk F rejects the hypothesis that instruments are weak at slightly above the 15% level.

Looking at the first column of the table, the coefficient on malaria is small and statistically insignificant for all OLS regressions, as expected by the biases already discussed. When turning to the IV specification in column 2, however, the coefficient on malaria becomes negative, large, and statistically significant for children, and marginally insignificant for adults (p-value for the adult regression: 0.10). Coefficients for women are slightly larger but within the standard error of those for men for both adults and children. Column 3 is the preferred specification. It shows that, controlling for the direct effect of elevation and slope on schooling, instrumented malaria remains strongly and negatively associated with lower schooling levels, with higher point estimates but also larger variance. Point estimates are higher for males than females, which is consistent with epidemiological evidence showing that Ethiopian males are more exposed to the disease (Yeshiwondim et al, 2009).[17] They are also higher for adults, as expected by the fact that they have completed education. Column 4 reports the results using the expanded set of instruments. The coefficients estimates remain very similar for children

[16] See appendix table 1 for the first stage and reduced form results.

[17] Boys and adult men spend more time in the fields than girls, who spend a larger fraction of their time at home. Since sleeping outside to protect the field is quite common, farm workers are more exposed to mosquito bites.

but weaken somewhat for adults. In particular, overall adult education is correlated with lower education (with a confidence level of 10%) but the correlation for male adults is now smaller and marginally insignificant (p-value on the coefficient of males is 0.12). LIML estimates (column 5) are larger in magnitude but confirm the interpretation from column 4. This is somewhat unsurprising, as IV estimates are biased towards the OLS when instruments are weak while LIML moves closer to the correct estimate. Taking the last column estimates, Overall, considering all estimated coefficients from panel A and B, the regressions indicate that moving from a no malaria village to one with average malaria (where the average is 5.7% for all villages, and 6.7% for those located below 2,500 meters) is associated with 0.26-0.56 fewer years of school for children, and 0.23-0.57 fewer years for adults.

6.2 Other outcomes

Table 7 considers the effect of topography on a number of other outcomes that might be affected by malaria incidence for villages located below 2,500 meters. First, one could expect child labor to be more prevalent in areas with more malaria if malaria drives up the demand for child labor, possibly because children may be sent to work in the fields to substitute for sick parents. In columns 1 and 2, I restrict the analysis to children to consider the incidence of child labor, measured as the proportion of children aged 10-17 who reported working in the prior seven days. Second, frequent malaria spells might reduce the earning ability of a household. For agricultural households, this might translate into more food insecurity in the short run. To verify this, I consider self reported instances of food insecurity (measured as the number of times villagers reported suffering a food shortage in the prior 5 years). Finally, over the long run, a more adverse environment should translate into lower levels of asset accumulation. To capture this, I consider the average value of the asset index. For all the outcome variables, I consider two 2SLS specifications: one where the sample is restricted to villages below 2,500 meters and the excluded instruments are elevation interacted with slope quintiles, and another with all villages where the excluded instruments also include the ”above 2,500 meter” dummy and separate elevation/slope interactions for villages above that elevation. I report both IV and LIML estimates for the latter.

The estimated correlations all move in the expected direction: malaria is associated with more child labor, more food insecurity, and lower levels of wealth. LIML estimates provide larger point estimates, but the specifications are statistically insignificant, so we cannot draw any relevant conclusion.

7 Conclusion

This paper presents correlates of malaria and development outcomes including schooling, mortality and asset accumulation using data from Ethiopia. The paper first provides evidence that malaria is strongly associated with topographical features. In particular, it makes use of the fact that malaria prevalence is sensitive to air temperature and to the presence of mosquito breeding grounds. Since temperature declines with elevation, and mosquito breeding grounds are less likely to form in sloped areas, it follows that elevation, slope, and the interaction between elevation and slope are potential time invariant predictors of malaria risk. The paper then uses these topographical features as instruments for malaria to reduce measurement error and reverse causality in a regression of malaria on local outcome variables from a large scale survey of Ethiopian villages. I find that Ethiopian villages that are less prone to malaria have higher schooling rates for both adults and children. I also find some suggestive (but ultimately inconclusive) evidence that malaria incidence is negatively correlated with asset accumulation and food security.

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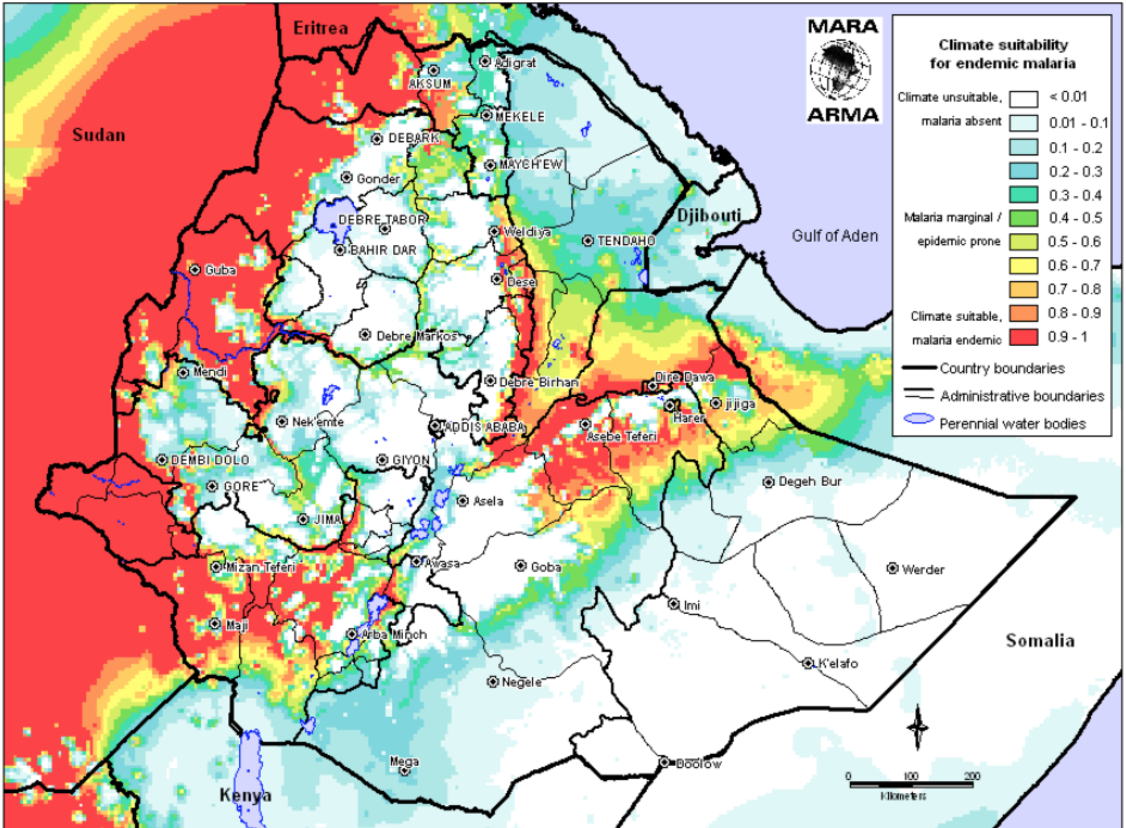
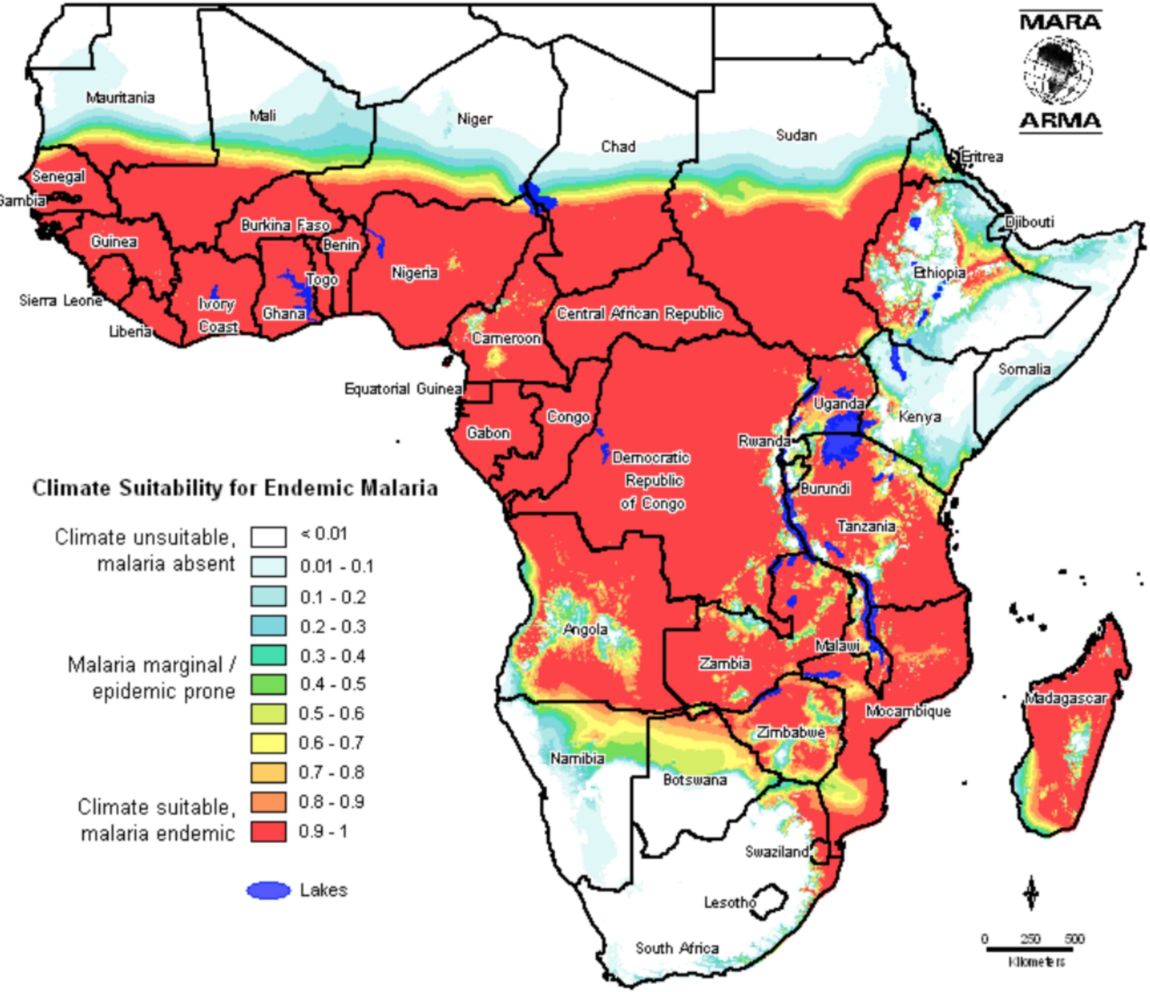
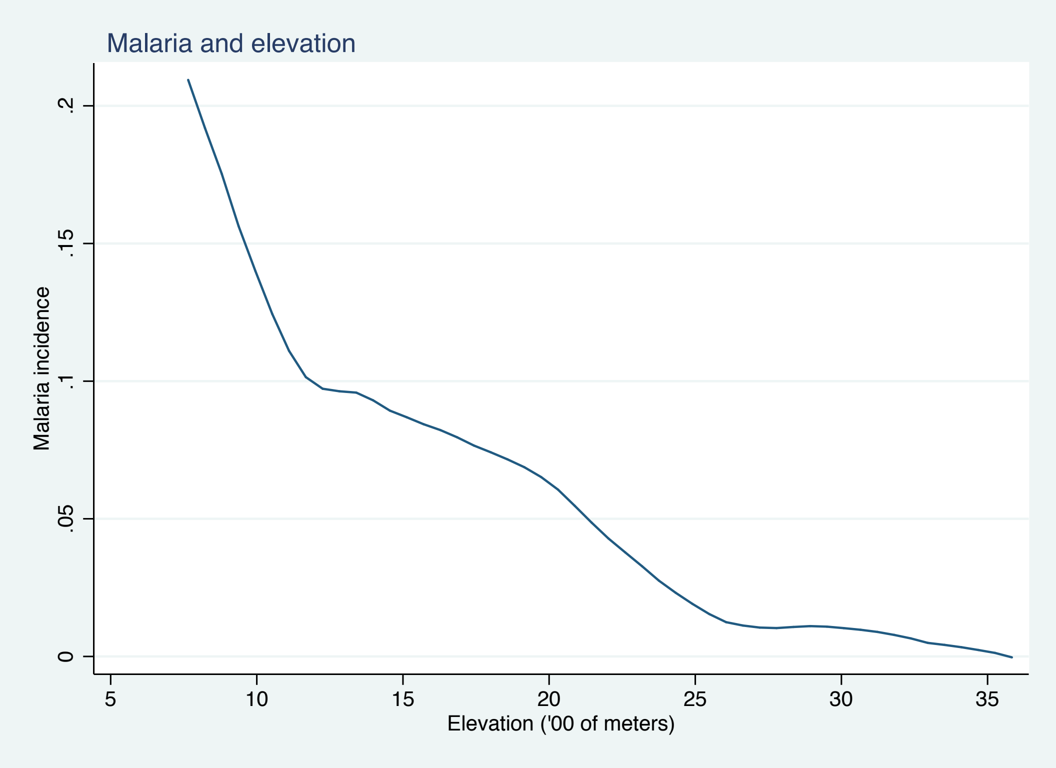
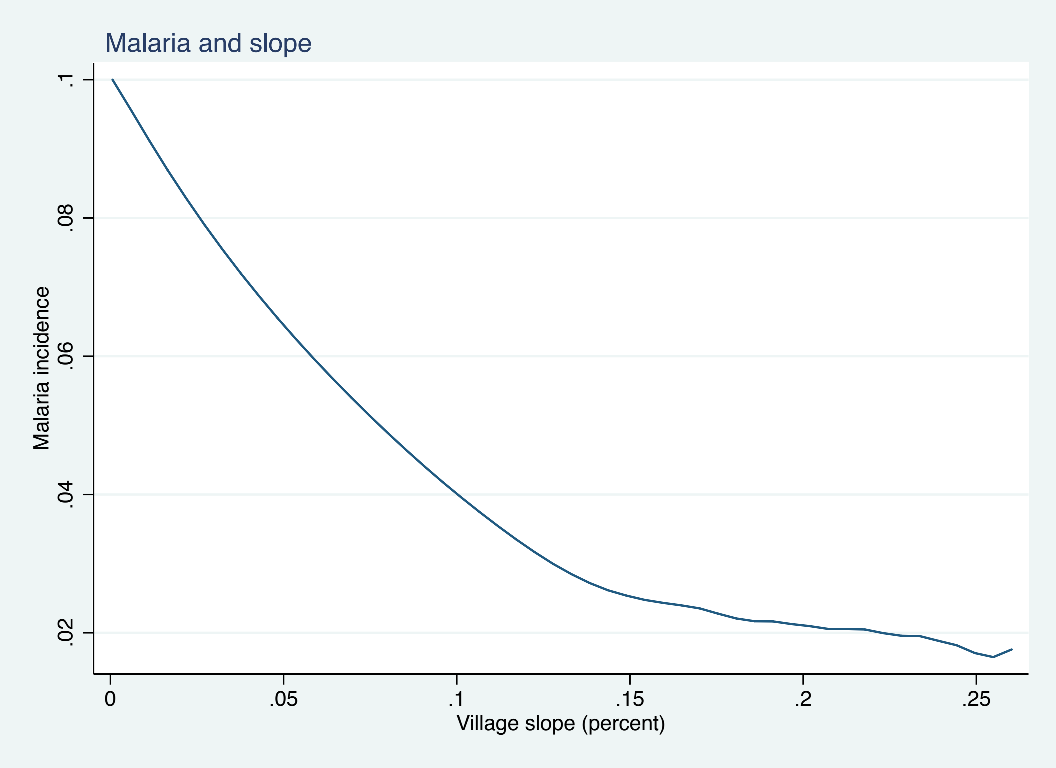
Ethiopia: Distribution of Endemic Malaria

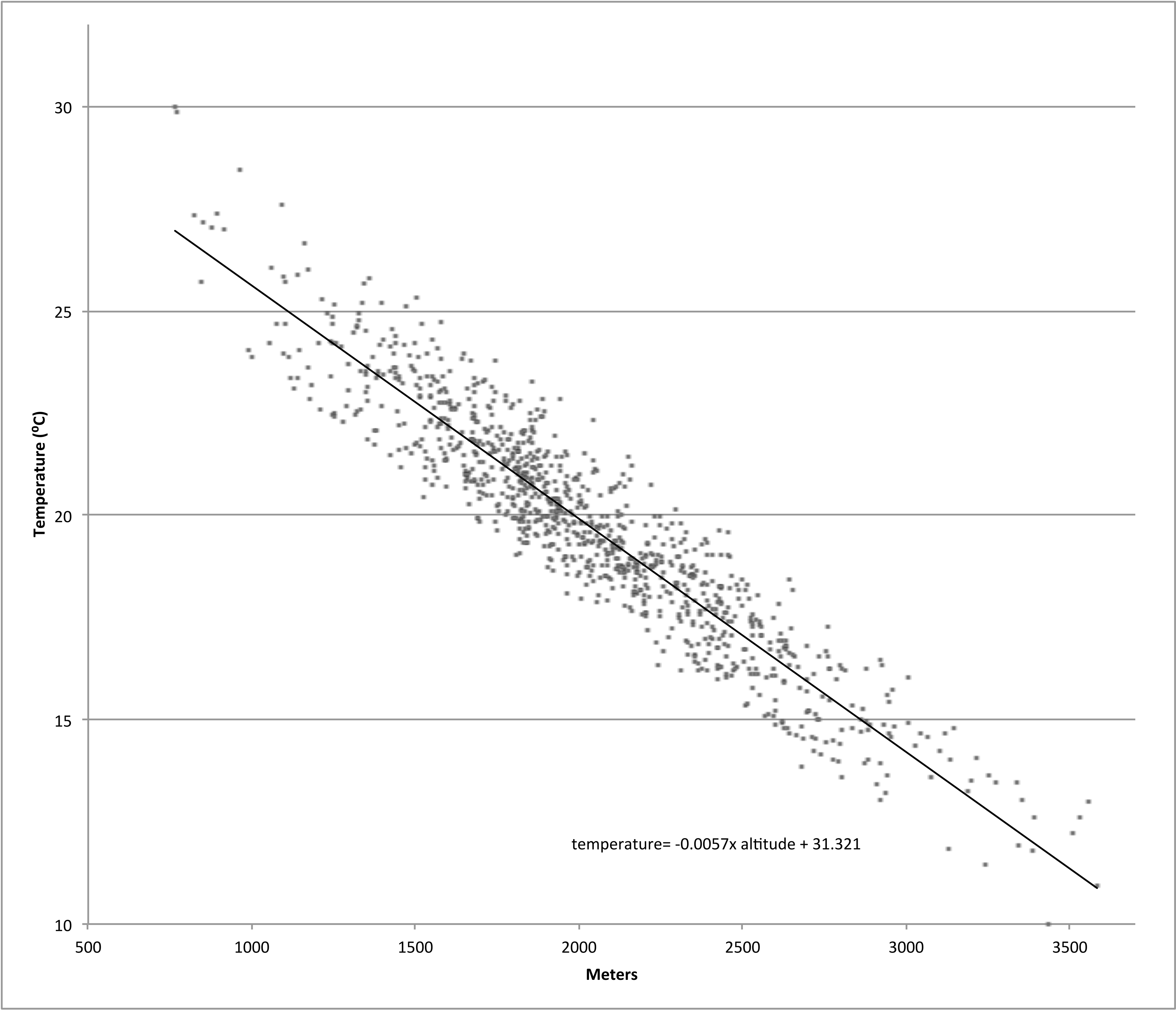


Distribution of Endemic Malaria




Malaria and elevation
Malaria incidence
0
.05
.1
.15
.2
5
10
15
20
25
30
35
Elevation ('00 of meters)


Malaria and slope
Malaria incidence
.1
.08
.06
.04
.02
0
.05
.1
.15
.2
.25
Village slope (percent)



30
25
20
15
10
Temperature (ºC)
500
1000
1500
2000
2500
3000
3500
Meters
temperature= -0.0057x altitude + 31.321

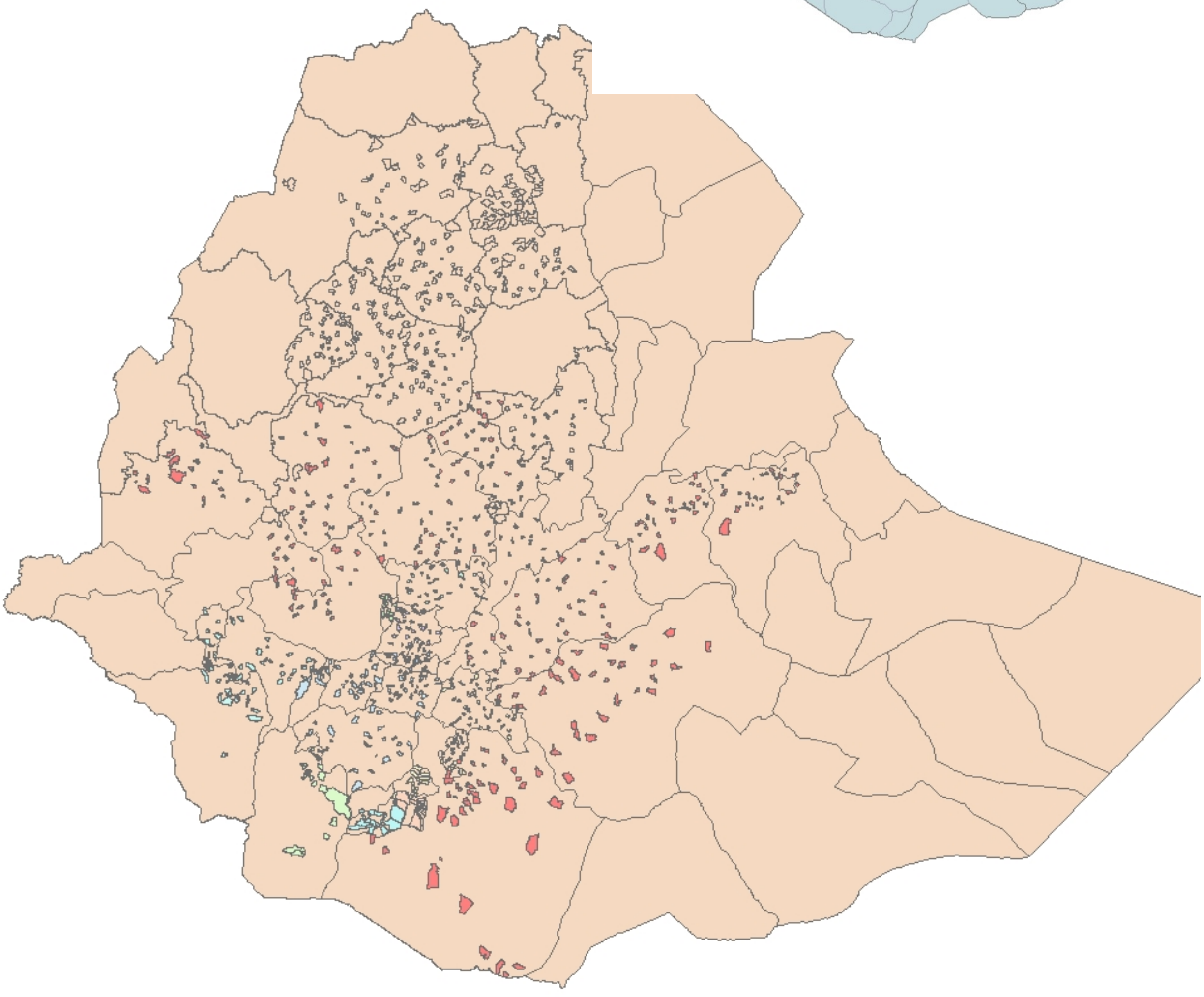


Table 1: Summary statistics

	All villages		Villages below 2,500 meters	
	Mean	St. Dev.	Mean	St. Dev.
Topographic characteristics				
Elevation ('00 meters)	20.36	4.64	18.99	3.47
Slope (percentage)	0.0675	0.0475	0.0667	0.0470
Rainfall	12.17	3.17	12.16	3.31
Recent reported village health problems:				
All sickness (% of village)	0.244	0.128	0.251	0.129
Malaria (% village)	0.057	0.095	0.066	0.100
Number of deaths in household (past 5 years)	0.287	0.425	0.292	0.446
Years of schooling:				
Children (age 7-19)	1.073	0.762	1.079	0.786
Adults (age >20)	1.058	0.931	1.078	0.955
Other outcomes				
Asset index	-0.975	0.600	-0.977	0.618
Labor past 7 days (age 10-17)	0.539	0.276	0.535	0.277
Food insecurity (past 5 years)	0.782	0.917	0.8082	0.9371
Household characteristics				
% farming households	0.922	0.110	0.921	0.111
% Landless	0.041	0.066	0.042	0.066
Tenure (years)	10.069	5.608	9.712	5.229
% Female head	0.229	0.131	0.228	0.132
Number of livestock	4.676	4.097	4.258	3.916
Number of oxen	0.927	0.657	0.913	0.595
Number of shocks (past 5 years)				
Floods	0.133	0.393	0.136	0.406
Droughts	0.417	0.798	0.434	0.816
Loss of livestock	0.386	0.618	0.387	0.619
Price/other shocks	0.048	0.234	0.049	0.250
Distances to facilities (in hrs)				
School	0.710	0.599	0.715	0.626
Health facilities	5.069	7.185	4.864	6.951
Observations (villages)	1000		844	

Table 2: Relationship between elevation, slope and reported health incidents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All sickness types		Malaria		Other health problem		Death	
Elevation ('00s meters)	-0.008***	-0.008***	-0.006***	-0.006***	-0.003	-0.002	-0.006	-0.006
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.011)	(0.010)
Elevation x 2,500 m		0.007		0.009***		-0.002		0.020
		(0.005)		(0.002)		(0.005)		(0.016)
Slope	-0.199	-0.152	-0.312***	-0.261***	0.111	0.107	-0.405	-0.276
	(0.151)	(0.120)	(0.081)	(0.060)	(0.123)	(0.104)	(0.351)	(0.297)
Sample of villages	<2,500m	All	<2,500m	All	<2,500m	All	<2,500m	All
Observations	844	1,000	844	1,000	844	1,000	844	1,000
R-squared	0.073	0.071	0.142	0.148	0.033	0.029	0.095	0.077
Province f.e.	YES	YES	YES	YES	YES	YES	YES	YES
P-value of F-test: Elevation + Elevation X Above = 0								
		0.927		0.1996		0.495		0.2635

OLS regressions at the village level. Odd columns include only villages with elevation <2,500 meters. Even columns include all villages in the sample. Dependent variable is the percentage of respondents reporting having some health problem in the prior 2 months. Death is the number of deaths in the family in the prior 5 years. Even columns include an above 2,500 meters dummy. Controls included: village average of rainfall, fraction agricultural households, fraction female headed household, average household size, number of livestock, oxen, wealth, land sizes, schooling of adult males and females, child age, and distance to schools and health clinics, number of droughts in the past 5 years. Errors clustered at the province level in parenthesis.

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Elevation, slope, and reported health incidents

	(1)	(2)	(3)	(4)
	All sickness types	Malaria	Other health problem	Death
Elevation	-0.006	-0.009**	0.003	-0.011
	(0.005)	(0.004)	(0.004)	(0.017)
Elevation X quintile:				
Slope 2	-0.001	-0.000	-0.001	0.006
	(0.005)	(0.004)	(0.004)	(0.015)
Slope 3	-0.004	-0.000	-0.004	-0.010
	(0.005)	(0.004)	(0.004)	(0.013)
Slope 4	-0.002	0.003	-0.005	0.004
	(0.005)	(0.004)	(0.004)	(0.017)
Slope 5	-0.001	0.007*	-0.008*	0.014
	(0.006)	(0.004)	(0.004)	(0.018)
Observations	844	844	844	844
R-squared	0.080	0.162	0.045	0.104
Number of waid	276	276	276	276
P-values of F-test: Elevation+ Elevation X quintile=0:				
Elev. 2nd quintile	0.105	0.004	0.678	0.679
Elev. 3rd quintile	0.001	0.000	0.551	0.043
Elev. 4th quintile	0.033	0.032	0.370	0.684
Elev. 5th quintile	0.056	0.507	0.065	0.831

Regressions on villages <2,500 only. Regression specification (1) is used in all columns. Controls include slope quintiles and other controls as in table 2. Errors clustered at the province level in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Topography correlates with other factors

Column title is dependent variable	(1) Floods	(2) Droughts	(3) Livestock losses	(4) Price shocks/ Other shocks	(5) School distance	(6) Health facility distance	(7) Tenure length	(8) Fraction landless	(9) Land sizes
Elevation	0.003	-0.073**	0.025	0.005	-0.020	-0.081	0.195	0.001	-0.001
	(0.016)	(0.033)	(0.030)	(0.014)	(0.021)	(0.341)	(0.191)	(0.003)	(0.036)
Elevation x:									
Slope 2	-0.010	0.053*	0.028	0.005	0.015	0.376	-0.031	0.004	-0.066*
	(0.014)	(0.028)	(0.025)	(0.017)	(0.020)	(0.326)	(0.180)	(0.003)	(0.037)
Slope 3	-0.006	0.048	0.002	-0.002	0.015	0.122	-0.138	0.001	-0.047
	(0.016)	(0.029)	(0.029)	(0.013)	(0.018)	(0.369)	(0.169)	(0.003)	(0.031)
Slope 4	0.001	0.063*	0.014	0.002	-0.037	0.024	-0.281	0.000	-0.037
	(0.016)	(0.035)	(0.030)	(0.013)	(0.033)	(0.342)	(0.193)	(0.003)	(0.033)
Slope 5	-0.015	0.056*	-0.049	-0.012	-0.030	-0.061	-0.270	-0.000	-0.077**
	(0.018)	(0.033)	(0.037)	(0.013)	(0.031)	(0.336)	(0.204)	(0.003)	(0.033)
Observations	844	844	844	844	844	844	844	844	844
R-squared	0.016	0.049	0.049	0.022	0.139	0.059	0.037	0.200	0.153
Province f.e.	YES	YES	YES	YES	YES	YES	YES	YES	YES
Mean dep. Var	0.132	0.414	0.386	0.048	0.712	4.83	9.72	0.052	2.88
P-value of F-test: Elevation + Elevation X Quintile = 0									
Elev., 2nd quantile=0	0.635	0.411	0.021	0.231	0.797	0.154	0.303	0.290	0.024
Elev., 3rd quantile=0	0.815	0.308	0.258	0.606	0.766	0.824	0.661	0.621	0.037
Elev., 4th quantile=0	0.720	0.732	0.079	0.316	0.071	0.739	0.566	0.577	0.134
Elev., 5th quantile=0	0.441	0.494	0.280	0.187	0.056	0.321	0.597	0.615	0.000

Sample of villages <2,500 meters. Shocks are the village average number of occurrences in the household in the prior 5 years. Tenure length is the number of years in the residence. Walking distance to facilities measured in hours. Land size is measured as quintiles of land size. Controls include slope quintiles and other controls as in table 2. Errors clustered at the province level.
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Relationship between village topography and schooling

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Villages <2,500 m		All villages		Villages < 2,500 m	
Average yrs. schooling	Children	Adults	Children	Adults	Children	Adults
Elevation	0.031**	0.045**	0.031***	0.036*	0.097***	0.075*
	(0.013)	(0.022)	(0.012)	(0.021)	(0.023)	(0.040)
Slope	-1.617**	-2.266**	-1.224*	-2.247**		
	(0.795)	(1.107)	(0.632)	(0.890)		
Elevation X:						
2,500 meters			-0.051**	-0.019		
			(0.024)	(0.027)		
Slope 2					-0.049**	0.003
					(0.021)	(0.033)
Slope 3					-0.067***	0.007
					(0.021)	(0.034)
Slope 4					-0.058**	-0.054
					(0.024)	(0.037)
Slope 5					-0.090***	-0.052
					(0.025)	(0.038)
Observations	844	844	1,000	1,000	844	844
R-squared	0.408	0.105	0.412	0.120	0.418	0.130
Number of provinces	276	276	295	295	276	276
P-Value of F-test: Elevation + Elevation X Quintile = 0						
Elev. 2nd quintile=0					0.002	0.010
Elev. 3rd quintile=0					0.084	0.011
Elev. 4th quintile=0					0.020	0.407
Elev. 5th quintile=0					0.706	0.352

OLS regressions at the village level. Column 3 and 4 include all villages, remaining columns exclude villages located above 2,500 meters. Controls for regressions on children schooling include controls from table 2. Columns 3 and 4 include an "above 2,500 meters" dummy. Columns 5 and 6 include slope quintiles. Controls for regressions on adult schooling include rainfall, average adult age, land size, distance to schools and health clinics, and number of droughts in the past 5 years. Errors clustered at the province level in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 6: IV estimates of malaria on schooling outcomes

	(1)	(2)	(3)	(4)	(5)
	OLS	IV	IV	IV	IV-LIML
Excluded instruments		Elevation only	Elevation X Slope quintiles	Elevation X Slope X Above	Elevation X Slope X Above
Panel A: Children's years of schooling					
All Children	-0.011	-5.414**	-4.489*	-4.512**	-9.791*
	(0.293)	(2.600)	(2.441)	(1.849)	(5.947)
R-squared	0.402	0.514	0.567	0.531	0.112
Boys	0.283	-6.124*	-6.840*	-5.516**	-11.890*
	(0.405)	(3.521)	(3.751)	(2.355)	(7.170)
R-squared	0.279	0.460	0.426	0.454	0.066
Girls	-0.165	-6.339*	-2.549	-4.528*	-6.873*
	(0.372)	(3.258)	(2.715)	(2.388)	(4.069)
R-squared	0.334	0.461	0.607	0.504	0.393
Panel B: Adults' years of schooling					
All adults	-0.065	-9.862	-8.587**	-4.031*	-6.095*
	(0.380)	(6.599)	(4.325)	(2.295)	(3.694)
R-squared	0.110	0.273	0.356	0.544	0.474
Male adults	-0.410	-6.324	-11.869*	-5.051	-10.459
	(0.558)	(7.493)	(6.643)	(3.275)	(8.248)
R-squared	0.072	0.561	0.412	0.572	0.454
Female adults	0.222	-9.601	-4.855	-2.219	-3.454
	(0.301)	(5.895)	(3.112)	(1.841)	(2.808)
R-squared	0.088	-0.100	0.365	0.485	0.437
Sample	<2,500 m	<2,500 m	<2,500 m	All	All
Observations	844	844	844	1000	1000
Province f.e.	YES	YES	YES	YES	YES

Table reports coefficients on instrumented village malaria.
Panel A controls as discussed in table 2. Panel B controls as listed in table 5.
Errors clustered at the province level in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Estimates of malaria on other outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Excluded instruments	Elevation X Slope quintiles	Elevation X Slope X Above 2,500m		Elevation X Slope quintiles	Elevation X Slope X Above 2,500m		Elevation X Slope quintiles	Elevation X Slope X Above 2,500m	
	IV	IV	IV-LIML	IV	IV	IV-LIML	IV	IV	IV-LIML
Column title is dependent variable	Child labor			Food insecurity			Asset index		
Instrumented malaria	0.354	1.078	2.043	3.783	2.354	4.380	-1.321	-1.346	-2.122
	(1.180)	(0.773)	(1.806)	(3.257)	(2.298)	(5.695)	(2.281)	(1.522)	(2.481)
Sample of villages	<2,500	All	All	<2,500	All	All	<2,500	All	All
Observations	843	999	999	844	1,000	1,000	844	1,000	1,000
R-squared	0.519	0.452	0.356	0.675	0.672	0.638	0.545	0.509	0.487

Columns 1-3 include child regression controls (see table 2). Remaining columns include adult regression controls (see table 5). Child labor is thefaction of children 10-17 who reported working in the prior 7 days. Food security refers to the average number of times households faced food shortages in the prior 5 years. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1