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The economic impacts of house screening against malaria transmission: Experimental evidence from eastern Zambia

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ABSTRACT

Malaria imposes an economic burden for human populations in many African countries, and this burden may be reduced through house screening initiatives. We use a randomized controlled trial to measure the economic impacts of house screening against malaria infection. We use a sample of 800 households from 89 villages in rural and peri-urban Zambia to collect baseline data in August 2019 and endline data in August 2020. The main outcome variables are (self-reported) malaria prevalence rates, labor supply, and income, and consider individual and household-level outcomes. House screening reduces malaria prevalence, the number of sick days due to malaria, and the number of malaria episodes. Impacts on adults are more pronounced than on children. In terms of economic impacts, house screening increases labor supply and (household) income. We find particularly large effects on labor supply for women household members. A cost-benefit analysis, based on estimated benefits and measured costs, suggests that the private benefits of house screening exceed the costs. While not all houses are suitable for house screening, we conclude that screening is a promising and cost-effective approach to reduce malaria infections.

1. Introduction

Malaria imposes a significant burden on a large proportion of the population of Sub-Saharan Africa (SSA). The disease caused 602,000 deaths in Africa in 2020, and its economic cost is around 12 billion dollars per year (World Health Organisation, 2021b). The economic effects of malaria are various (Arrow et al., 2004; Barofsky et al., 2015; Sicuri et al., 2013). The most obvious effect arises from the death of economically productive household members in their prime-age or of children—robbing households of the much-needed stock of human capital. Malaria also imposes economic burdens through loss of productive time, causing a decline in income from farm and off-farm activities. Costs may also emerge due to medical expenses.

In the SSA region and elsewhere, measures to control malaria have yielded considerable success. A combination of interventions, including Long Lasting Insecticide Treated Nets (LLINs) and Indoor Residual Spraying (IRS), are the main drivers of this progress (Pinder et al., 2016; USAID, 2017). The number of malaria cases in several SSA countries fell between 2010 and 2015, mainly due to vector control interventions. The number of malaria in-patient cases in Zambia reduced by 52% (USAID, 2017). However, these hard-won gains may be reversed because the efficacy of LLIN and IRS depends on the use of insecticides, which has resulted in the emergence of insecticide resistance (Pinder et al., 2016).

The emergence of resistence presents a threat to the efficacy of LLINs and IRS, leading to renewed calls for additional vector control interventions (Chanda et al., 2015; Kirby et al., 2009). Increased resistance may necessitate more expensive alternative insecticides, which would make IRS more costly (Killeen et al., 2019). Another concern is the low durability of LLINs. The lifetime of such bed nets is estimated to be less than two years due to poor fabrics used in production (Hakizimana et al., 2014). The physical durability of LLINs is also limited because house occupants must enter and exit enclosed sleeping spaces every night, resulting in "wear and tear" (Killeen et al., 2019). As a result, LLINs and IRS need to be complemented with more sustainable and effective approaches (Killeen et al., 2019). Additional vector control methods against malaria transmission are currently explored (e.g., Kirby et al.,

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2009; Pinder et al., 2016; World Health Organisation, 2021a). House screening (HS) is one of these methods. It can be provided as a stand-alone intervention (i.e. without LLIN or IRS) but can also be combined with LLIN or IRS (e.g., Getawen et al., 2018; Pinder et al., 2016). Important sponsors are donor agencies with an interest in public health, such as the WHO, private donors and development agencies, and research funding agencies (such as MRC, Wellcome Trust, etc.).

House screening aims to contribute to mosquito-proofed housing and involves closing eave gaps and placing fine wire mesh (netting screen) over windows, doors, eaves, and other ventilation openings. The intervention prevents entry of mosquitoes in houses, averts mosquito bites and thereby prevents diseases such as malaria. A number of trials on the effectiveness of HS—mainly focusing on entomological and clinical outcomes—have been conducted in SSA (Kua and Lee, 2021; Tusting et al., 2015). Some studies demonstrate the efficacy of HS (see Getawen et al., 2018; Killeen et al., 2019; Lindsay et al., 2003; Massebo and Lindtjørn, 2013; Mburu et al., 2018; Ng'ang'a et al., 2020; Njie et al., 2014), but other produce less encouraging results. For example, Pinder et al. (2021) find that improved housing did not provide incremental protection against malaria in The Gambia—a context of low seasonal transmission with high coverage of LLINs, IRS, and malaria chemoprevention in the control group ("best practices"). Kirby et al. (2009) found the prevalence of anemia in children from screened and unscreened houses to be similar, perhaps because of behavioral factors attenuating the impact of screens (e.g., reduced use of bednets, and screens left open during part of the day). HS has not yet been adopted as part of the mainstream vector management tools for malaria control in most countries. However, the World Health Organization conditionally recommends HS for the prevention and control of malaria (World Health Organization, 2021a).

HS has a number of advantages. First, when residing indoors, every household member is equally protected from mosquito bites—minimizing intra-household inequality of access to protection. Second, it is an environmentally friendly method that does not need insecticides. Third, screening materials may last longer than bed nets because they are left relatively undisturbed once installed (Killeen et al., 2019; Kirby et al., 2009). Existing studies consider entomological outcomes such as indoor mosquito presence; clinical outcomes, such as prevalence of malaria and malaria-induced anemia; and socio-economic outcomes, such as social acceptability, durability and cost of the intervention. However, most of these studies focused on measuring the effectiveness of HS on indoor mosquito densities and malaria morbidity (particularly in children), and little evidence exists on the economic effects of HS.

The objectives of this study are (i) to determine the impact of house screening on (*self-reported*) malaria prevalence and socio-economic outcomes, and (ii) to evaluate the costs and benefits of the intervention. We analyze how HS affects labor supply and income in the short term. We tried to probe the impact of HS on children's school attendance but failed because schools were closed during the time of our field experiment due to the COVID-19 pandemic. We also assess if the impact of HS varies across individual household members, distinguishing between male and female members and between adults and children. The impact of screening may vary across socio-demographic groups due to differences in exposure and differences in "economic roles" within the household—for example, farm-production, off-farm production, and care-taking (e.g. Diiro et al., 2022). Finally, upon combining our impact estimates with screening cost data collected during the intervention, we ask whether the economic benefits of HS outweigh the costs within four years of providing the intervention.

We set up a Randomized Controlled Trial (RCT) in Zambia, and randomly assigned households to the treatment or control group. Households in the treatment arm received house screens plus bed nets, and households in the control only received bed nets. We therefore measure a *conditional* treatment effect – the effect of screening for households that already possess at least one bed net. We did not measure at endline whether the households actually used the bed net they received, so we cannot control for actual LLIN usage (which is a limitation of the study). The. Primary outcome of HS is self-reported malaria prevalence, and important secondary outcomes are labor supply and income. Further, to enable a cost-benefit analysis we tracked the costs of screening. The empirical results are encouraging. We find that HS document a reduction in malaria prevalence during the peak transmission season. HS also reduced the number of days an individual was reported ill with malaria, and the number of malaria episodes experienced by individuals. This reduction in malaria prevalence generated short-term economic gains. HS increased labor supply by nearly two days per adult or almost five days per household during the peak malaria transmission season. Household income increased by US$55, representing a nearly 40% gain in household monetary income. Our cost-benefit analysis suggests the net present value of house screening is positive.

Our results complement the existing literature on the impact of malaria on economic development (see Arrow et al., 2004; Barofsky et al., 2015). A shortcoming of many existing studies is their inability to measure the causal effects of malaria as they rely on non-experimental approaches — measuring associations rather than causality. A few exceptions include studies that use natural experiments (e.g., Bleakley, 2003; Barofsky et al., 2015) and randomized experiments (Fink and Masiye, 2015; Pinder et al., 2016, 2021). We further document the heterogeneous impacts across household members, focus on impacts conditional on also using bed nets, and generate evidence to inform policymakers about cost-effectiveness.

2. Research design and non-compliance to randomization

We implemented our study in Nyimba District, in the Eastern Province of Zambia. Ethical approval was obtained from the Ethical Review Board, ERES Coverge IRB in Zambia (Ref: 28-October-007). Nyimba District is predominantly a rural district with an estimated population of nearly 110,000 persons and a high rate of malaria transmission—20% using RDTs (Ministry of Health Zambia, 2018). A total of 89 villages were included in the study. The main economic activity in these villages is subsistence farming, with farmers selling surplus crops in local markets. Maize and groundnuts are the major crops grown.

In March 2019, we developed a sampling frame of 3000 households. Next, we randomly selected 800 households from the sampling frame, half of which were drawn from a peri-urban region of the district (relatively close to government health facilities) and the other half drawn from a more rural region of the district. We used the following inclusion criteria: (i) at least two children with ages ranging between 6 months and 13 years; (ii) houses should not be already screened; and (iii) a minimum distance of 50 m between any two houses in the study to avoid spillovers. Households were randomly assigned to the treatment arm (400 households) or the control arm (400 households), where we stratified on the region of participants.

We performed a power calculation, which suggested that the minimum sample size required to detect a 15% effect size of HS on self-reported malaria prevalence of all household members (with $\alpha = 0.05$, $\beta = 0.80$, average household size is 5.2 members). In the absence of intra-household correlation, we need a minimum sample size of 303 households. If we conservatively apply an intra-household correlation coefficient equal to 0.4, we obtain a minimum sample size of 400 households per experimental arm, or 800 households in total.

Implementation started in December 2019. Treatment households received LLINs and had potential mosquito entry points of their houses sealed or screened free of charge. Control households received one LLIN per household because we decided against leaving these households unprotected. This approach enables estimation of a conditional treatment effect—the effect of screening on households that already have one bed net. The screening was implemented by local artisans (mainly carpenters), who received training and instructions. A small mobile team of six carpenters screened all houses. It took about 90 min to screen a

house. Materials used for house screening included wire mesh as the screening material, wood (timber), cement, sand and accessories such as wire nails, soft wire, and door hinges (see appendix B). The materials were not treated with insecticides. IRS was not implemented in the study region during the period of the study, but other malaria prevention methods such as Intermittent Preventive Treatment (IPTPp) were continued at clinics located in the study area. Refer to appendix C for more information about the sampling plan and implementation.

While teams of artisans received instructions about which houses to screen, they deviated from the plan "in the field" after learning that some "traditional houses" could not be screened. These houses had too many eaves, openings and holes (typically in the roof). If screening was not feasible, the team screened a house from the control group instead. Specifically, 530 households received treatment (or not) following their initial assignment, and 135 households from the treatment group "swapped places" with households from the control group. This violation of the design would introduce bias in our impact estimates if we would estimate an average treatment effect based on actual treatment because "high-quality houses" inhabited by relatively well-off households were more likely to receive treatment than "low-quality houses." Below we discuss how we address this challenge to unbiased attribution.

The study was designed prior to the emergence of covid-19, but its implementation overlapped with the pandemic. The covid-19 pandemic complicated implementation of the screening intervention (i.e., the movement of artisans between villages) and moderated its impact (i.e. schools were closed, so impacts on education could not be measured). One might also be concerned that the pandemic affected measurement of malaria prevalence if individuals confused covid-19 for malaria. However, these challenged did not affect the main outcomes of the study, except the education outcomes. Travel restrictions caused mild delays in implementation, but screening was completed before the start of the main malaria season. While some household members may be confused about the disease they contracted, the great majority of respondents is quite familiar with malaria and its symptoms. Moreover, data were collected by trained enumerators with a background in medicine who helped respondents to provide the right answer in case of uncertainty.

3. Data and identification

3.1. Data collection

We collected a panel of household data with two waves. Baseline survey data were collected from 800 participating households between July and August 2019. This survey included questions to capture characteristics of the household and individual household members, malaria prevalence (using recall method), and certain behavioral variables. At baseline, we also used Rapid Diagnostic Tests (RDT) to measure malaria among children. When a child tested positive by RDT we provided them with artemisinin-based combination therapy (ACT) and took them to the nearest health facility if they had complicated malaria. This paper defines children as individuals between 6 months and 13 years, and adults as people older than 13 years. Unlike recall methods, which can be used to collect data for a time interval, RDT only measures *current* malaria infections or illness at the moment of measurement. It provides a "snapshot" with relatively little measurement error and is therefore well suitable to examine "balance" between treatment and control group. However, RDTs are expensive, and our budget did not allow collecting endline data using the same method. Instead, we collected malaria prevalence among children at endline using self-reported data.

We collected end-line data using a second survey in August 2020. Our outcome variables refer to the peak malaria season (November 2019 and May 2020), which is also the primary agricultural season and the peak season in terms of demand for agricultural labor. We collected individual data on malaria prevalence, days of sickness, labor supply, and income. In addition, we kept track of screening costs. We use self-reported malaria during the peak malaria season as the dependent variable. To increase the reliability of these data we used trained health staff as data collectors. These health staff had experience probing respondents to ensure respondents do not confuse malaria with other illnesses (including covid-19). We used self-reported data as they enable capturing malaria during the entire peak season (rather than at a single moment in time), matching the time frame of our economic variables. Other studies also assessed malaria prevalence using self-reported survey methods (e.g., Dhewantara et al., 2019; Ipa et al., 2020; Keating et al., 2005).

We used survey questions to measure (monetary) household income. We first asked households to list the agricultural activities (e.g., cropping and livestock raising) and off-farm activities that they engaged in between May 2020 and August 2020, and then asked to provide an estimate of total income per subcategory. We next summed agricultural and non-agricultural income to obtain a measure of total household income during the study period. We transform household income by taking the natural logarithm to account for skewness in the distribution.

Table 1 shows the baseline values of our variables. The first panel summarizes outcome variables, including malaria prevalence (self-reported for adults and RDT-confirmed for children), labor supply, and income. The second panel summarizes our covariates. These are individual and household characteristics, including household demographics, assets, housing conditions, malaria prevention measures, and measures of household behavior. As mentioned, non-compliance occurred due to the implementing field team. Therefore, we present two comparisons: the first one based on (initial) random assignment to treatment ($T = z_i$), and the second one based on actual receipt of treatment ($T = d_i$). We use t-tests to check the balance between the treatment and control group, based on both classifications.

As is evident, random *assignment* resulted in balance for most of our variables. A few variables were significantly different, presumably due to chance. However, and not unexpectedly, the same is not true for the classification based on actual *treatment*. While the outcome variables are rather similar, we observe significant differences for many of our covariates—especially those related to housing conditions, assets, and self-reported baseline malaria prevalence. Simply comparing outcomes across treated and untreated households would produce biased impact estimates if these variables were correlated with our outcome variables (which is likely).

3.2. Empirical estimation

We use the Local Average Treatment Effect (LATE) estimator. The LATE addresses the endogeneity introduced by non-random non-compliance during HS implementation. It measures the effect of screening for the sub-sample of complying households, or the effect for the subsample of households for which the *implementing team in the field complied with instructions*—those households living in houses that can potentially be screened (and not in traditional houses with too many openings in the roof or elsewhere). It is evident that care should be taken to extend our results to other social groups.

We estimate the LATE by using random assignment, z_i, as an instrumental variable (IV) to predict the receipt of actual treatment, d_i (where $z_i = 1$ if the household was assigned to treatment, and $z_i = 0$ otherwise). We estimate impact through a system of two linear equations (2SLS):

$$d_{ik} = \rho_{11} + \pi_{11} z_{ik} + \pi_{12} V_k + \vartheta_{1ik}, \text{and} \quad (1)$$

$$Y_{ik} = \rho_{21} + \pi_{21} d^*_{ik} + \pi_{22} V_k + \vartheta_{2ik}, \quad (2)$$

where Y_i is the dependent variable of household i in village k, V_k is a vector of village fixed effects accounting for variation in geophysical and governance conditions. In (1), ρ_{11} and ϑ_{1ik} are the constant and error term, respectively. Equation (2) explains variation in outcomes by

Table 1
Baseline characteristics of the treatment and control groups.

Variables	Random assignment ($T = z_i$)			Actual treatment ($T = d_i$)		
	Treatment	Control	P-value	Treatment	Control	P-value
PANEL A: Outcome Variables						
Malaria prevalence:						
Malaria incidence-adults (1 = yes)	0.436	0.449	0.5597	0.412	0.471	0.0115**
Malaria incidence (RDT)-children (1 = positive)	0.164	0.186	0.1795	0.170	0.179	0.626
Number of malaria episodes	1.744	1.689	0.4500	1.721	1.719	0.976
Labor supply:						
Days not working due to malaria	5.263	5.500	0.4022	5.185	5.538	0.209
Days partially working due to malaria	1.600	2.114	0.0802*	1.774	1.845	0.805
Days lost taking care of sick	5.761	6.254	0.2050	6.099	6.671	0.392
School attendance:						
Missed school due to malaria (1 = yes)	0.582	0.492	0.0149**	0.580	0.501	0.030**
School days absent last term	5.264	5.276	0.9812	5.192	5.367	0.724
Income:						
Total income (USD)	185	134	0.0182**	169	155	0.524
Farm income (USD)	92	65	0.0788*	89	71	0.233
Non-farm income (USD)	93	69	0.1086	80	84	0.795
PANEL B: Co-variates						
Demographics:						
Age of household head	41.336	41.325	0.9913	41.053	41.604	0.574
Female head (1 = yes)	0.271	0.261	0.7269	0.270	0.263	0.818
Household size	5.461	5.243	0.1434	5.593	5.138	0.002***
Education (1 = None)	0.231	0.206	0.4107	0.193	0.246	0.076*
Education (1 = primary)	0.575	0.579	0.9155	0.616	0.539	0.029**
Education (1 = secondary)	0.183	0.212	0.3034	0.181	0.211	0.290
Education (1 = tertiary)	0.011	0.003	0.1661	0.010	0.005	0.403
Assets:						
Agricultural land size (Ha)	3.496	3.166	0.0389**	3.442	3.256	0.241
Total Livestock Units (TLUs)	1.984	1.678	0.1462	2.119	1.574	0.011***
Have a radio (1 = yes)	0.274	0.282	0.7906	0.323	0.233	0.0046***
Have a mobile phone (1 = yes)	0.740	0.732	0.7977	0.763	0.709	0.084*
Housing conditions:						
Wall material (1 = bricks)	0.511	0.497	0.6907	0.651	0.361	<0.001***
Roofing materials (1 = iron sheets)	0.598	0.562	0.3074	0.791	0.376	<0.001***
Number of sleeping spaces	2.639	2.627	0.9093	2.779	2.491	0.007***
Malaria prevention:						
Have a bed net (1 = yes)	0.470	0.470	0.9689	0.506	0.433	0.040***
Slept under bed net (1 = yes)	0.331	0.338	0.6272	0.348	0.319	0.046**
Behavior:						
Hours spent indoors	10.43	10.56	0.4673	10.57	10.40	0.328

Notes: *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$.

predicted treatment (based on results of (1)) and village fixed effects. We also estimate individual-level regression models, and then include household-level fixed effects and cluster standard errors at the household level. Some of our outcome variables are binary. We estimate such models using the Linear Probability Model (LPM) for ease of interpretation as well as clustering of standard errors. The drawback is that probabilities are not restricted to the interval between 0 and 1—an empirical issue to which we return below. Our coefficient of interest is π_{21}. Observe that, by design, our instrument z is independent of end-line outcomes, so the exclusion restriction is automatically satisfied. We report the results of models without covariates, but results are qualitatively unaffected if we control for baseline demographics (the precision of our estimates slightly improves when including covariates). We also explored non-linear models (probit, logit, Poisson), and found that results are qualitatively robust (results not shown but available on request).

As additional robustness checks we estimated intention-to-treat (ITT) models, regressing outcomes on random assignment, and difference-in-differences (DiD) models for the subset of dependent variables for which we also have baseline values. Overall, results were qualitatively similar to the ones reported below. The ITT estimates are generally smaller, which reflects the endogeneity bias due to randomization failure—poorly constructed houses assigned to treatment were less likely to receive screens. We refrain from reporting these estimates, but they are available on request. Finally, to evaluate whether the benefits of providing the house screening intervention outweigh the costs, we use a cost-benefit approach, and compare the estimated income gains due to screening with the measured costs. We assume that HS offers protection for four years (Kirby et al., 2009):

$$NPV_{ij} = \sum_{t=1}^{4} \frac{B - mc}{(1+r)^t} - C. \quad (4)$$

Benefits B in equation (5)is derived from our LATE estimates for labor supply, where extra working days are converted into income by multiplying the number of days by the local daily wage. This is a wage valuation approach similar to previous studies (e.g., Ungar et al., 2000). We also use a direct estimate of income—self-reported by respondents. The income gain from HS as the percentage change from the mean of the control group can be converted to a dollar amount.

We also measure the one-time screening costs per household, C, based on actual construction costs incurred during the experiment (materials, labor and transportation). We include maintenance costs of screening materials, mc, incurred annually by the household, and estimate these costs at 5% of construction costs C. To estimate the Net Present Value (NPV) of screening, we discount future benefits at a rate of $r = 3\%$ (Sicuri et al., 2013). As a robustness analysis we also use a discount rate of 10% and maintenance costs of 3 and 10% of the construction cost.

4. Results

4.1. Summary statistics

We discuss summary statistics for our main outcome variables at baseline—aggregating participants from the treated and control groups (as introduced in Table 1). Overall, *self-reported* malaria prevalence during the peak season stood at 44.2%. Based on RDT tests conducted at baseline, malaria prevalence for children was 17.4% (a snapshot value). The average number of malaria episodes for adults was 1.72 during the previous peak malaria transmission period. Over the same period, the average number of days an adult person did not work at all due to malaria was 5.37 days, and adults lost an additional 1.81 days because they could only work "part-time" due to malaria. The average number of days lost because of care provision responsibilities for sick family members was 6.0 days. Summing the number of days that adults were unable to work, and assuming the various categories are mutually exclusive, the average reduction in labor supply is 13.18 days. Since there are 2.7 adults per household, the total number of work days per season lost due to malaria equals 36. Some 54.3% of school-going children were reported to have missed school the previous term due to malaria. On average, they missed 5.26 days during the term.

Another important variable is household income. Average monetary income for the main crop marketing period was US$162 at baseline. This sum was almost equally derived from agriculture (US$80) and non-agricultural sources (US$82). Observe that this sum is an underestimate of full household income, as most households also engage in subsistence agriculture.

4.2. Impact of house screening on self-reported malaria prevalence

Table 2 summarizes results for the pooled sample, for adults and children separately, and for men and women separately. The linear probability model yields plausible predictions for our outcome variables, and only a handful of observations (30) were outside the admissible range of 0–1. In Appendix Table A1 we report first stage outcomes associated with the 2SLS model. Random assignment enters significantly for all samples and the partial F-statistic indicates our instrument is strong.

House Screening significantly reduces the prevalence of *self-reported* malaria. The LATE estimate indicates that HS reduced the probability of malaria infection by 18.4 percentage points for the full sample. This represents a change from the estimated predicted probability of 0.46 to 0.28 (computed using the "*mchange*" command in Stata 15). The prevalence rate for the control group was nearly 41%, so this implies a sizable reduction. As a robustness analysis we report results for different minimum distances between treated and control houses in appendix Table A2 (100 and 200 m, instead of 50 m), and find that regression coefficients are essentially unaffected. This suggests that spillover effects are minimal. Spillover effects could occur if mosquitos barred from entering screened houses would enter control group houses instead.

We find statistically significant impacts for both adults and children. However, HS has a larger impact on the health status of adults than children. Based on the LATE, screening reduced the probability of malaria infection by 22.7 percentage points for adults compared to 14.3 percentage points for children. The predicted probability of children's malaria infection is reduced from 0.42 to 0.28, and the predicted probability of adults' malaria infection reduced from 0.40 to 0.17. This is a matter of concern because children, especially those under the age of 5 years, suffer more from the adverse effects of malaria transmission, and have a greater mortality risk (Arrow et al., 2004; Sicuri et al., 2013).

In Table 3 we probe the underlying reason for the difference in results between adults and children. A plausible explanation is based on differences in individual behavior. During the baseline and endline surveys, we measured the amount of time each household member spent indoors as a potential mediating variable of the HS intervention. Table 3 indeed shows that children spent less time indoors at night as a result of HS. The dependent variable indicates the number of hours spent indoors the night before the interview. On average, children in the treatment group spent 34 min less indoors at night. In contrast, there was no discernible change in behavior by adults in response to HS. By spending more time outdoors at night, children may have been more exposed to mosquitos, which may explain the attenuated impact of HS relative to adults. A possible reason why children spend less time indoors after screening is the hotter indoor temperature in screened houses. In the Gambia, screened houses were 0.5°C-1.5 °C hotter at night than houses in the control group (Kirby et al. 2010; Jatta et al., 2018), unless improved ventilation measures are also introduced (Jatta et al., 2018).

Table 4 presents the results of the impact of HS on the number of days that individual household members were reported to be ill with malaria during the peak transmission period. Screening reduced the number of sick days by 1.43 days during the peak transmission season—not significantly different for adults and children. The average number of days a person from the control group was ill with malaria was 5.7 days, so HS reduced the number of sick days by an average of 25%.

We also assessed the impact of HS on the number of malaria episodes.

Table 2
House screening and malaria prevalence (2SLS Regression).

	Full sample	Children (≤13 yrs)	Adults (>13 yrs)	Adult males	Adult females
House screening	−0.18**	−0.14*	−0.23***	−0.276**	−0.190**
	(0.074)	(0.086)	(0.084)	(0.118)	(0.0938)
95% Conf. Interval	−0.33 to −0.04	−0.31 to −0.03	−0.39 to −0.06	−0.51 to −0.04	−0.37 to-0.01
Constant	0.280**	0.170*	0.369**	0.444**	0.298*
	(0.121)	(0.097)	(0.152)	(0.192)	(0.174)
Co-variates	No	No	No	No	No
Village F.E.	Yes	Yes	Yes	Yes	Yes
Mean prevalence control group (%)	40.80	41.79	39.83	41.87	39.49
N	3703	1818	1797	789	1008
Partial F-Statistic	23.58	20.86	20.95	33.86	19.66
R-squared	0.104	0.150	0.113	0.149	0.141

Note: LATE results. Robust standard errors clustered at the household level are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$. The period for the outcome variable is November 2019 to May 2020.

Table 3
House screening and time spent indoors (2SLS regression).

	Children (≤13 yrs)	Adults (>13 yrs)	Adult males	Adult females
House screening	−0.559**	0.060	0.038	0.0363
	(0.305)	(0.349)	(0.499)	(0.406)
95% Conf. Interval	−1.16 to −0.04	−0.62 to 0.74	−0.940 to 1.02	−0.760 to 0.832
Constant	10.92***	9.806***	9.210 ***	10.49***
	(0.370)	(0.365)	(0.410)	(0.259)
Co-variates	No	No	No	No
Village fixed effects	Yes	Yes	Yes	Yes
Mean control group	11.40	10.32	10.06	10.51
N	1775	1752	759	993
Partial F-Statistic	20.35	20.47	33.78	19.25
R-squared	0.092	0.083	0.144	0.094

Note: LATE results. Robust standard errors clustered at the household level in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$. The period was the night before the interview. The unit of measurement is hours.

Table 4
House screening and the number of days of malaria sickness (2SLS Regression).

	Full sample	Children (≤13 yrs)	Adults (>13 yrs)	Adult males	Adult females
House screening	−1.426***	−1.474 **	−1.404**	−0.972	−1.612**
	(0.512)	(0.628)	(0.585)	(0.772)	(0.716)
95% Conf. Interval	−2.43 to −0.42	−2.70 to −0.24	−2.55 to −0.26	−2.48 to 0.54	−3.01 to −0.21
Constant	1.996**	1.471	2.472**	2.880*	1.903*
	(1.037)	(1.018)	(1.121)	(1.744)	(1.109)
Co-variates	No	No	No	No	No
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Mean control group	5.66	5.64	5.69	5.73	5.67
N	3703	1818	1885	837	1048
Partial F-Statistic	23.58	20.86	21.75	35.25	20.52
R-squared	0.075	0.117	0.073	0.128	0.085

Note: LATE results. Robust standard errors clustered at household level in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$. The period for the outcome variable is November 2019 to May 2020.

Screening reduced the number of malaria episodes by 0.35, based on the full sample (Table 5). Considering the mean number of episodes for the control group (nearly two episodes during the peak season), this implies a 17.5% reduction. Again, we find that the results for children are attenuated. While screening reduced the number of malaria episodes by 0.40 episodes in adults, the reduction among children is 0.30 (a 15% reduction compared to the control group's mean).

Tables 2–5 also suggest the impacts of HS are mediated by gender. Male adults experienced a 28-percentage points reduction in the probability of malaria infection compared to a 19 percentage point reduction for females. This may reflect differences in gender roles, including different responsibilities for (outdoor) cooking and animal care in the evening. However, we also find that the reduction in the number of malaria sick days is significantly *larger* for females (1.61 days). We speculate that this may reflect that women sometimes have a higher disposition to suffer from more complicated or "severe" malaria cases—for example when pregnant or lactating (Kovacs et al., 2015). When pregnant, women are particularly at risk of malaria, as they are of any infection. The impact of HS on the number of malaria episodes is very similar for both genders. We conclude that the gender-mediated impact of house screening is an interesting topic for future research.

4.3. House screening and labor supply

We measure labor supply in terms of full-time working days. Malaria affects the labor supply because people may be too sick to work or because healthy individuals take care of relatives sick with malaria. The full effect on labor supply is the sum of the effect of workdays lost partially or completely due to one's illness and workdays lost because of providing care. Table 6 shows this impact of HS, where we also disaggregate the data by gender. The outcomes capture differences in exposure but also reflect gender roles in care provision. We assume only adults, older than 13 years, engage in working and disregard potential labor supplied by children.

Table 6
House screening, labor supply, and income (2SLS Regression).

	Days not working because of malaria			Household income
	Full sample	Male household members	Female household members	Full sample
House screening	−1.82**	−0.59	−2.56*	0.396*
	(1.09)	(1.37)	(1.30)	(0.231)
95% Conf. Interval	−3.97 to 0.32	−3.26 to 2.09	−5.11 to −0.01	−0.06 to 0.85
Constant	3.48**	4.08**	2.51*	7.47 ***
	(1.38)	(1.84)	(1.45)	(0.128)
Village fixed effects	Yes	Yes	Yes	Yes
Covariates	No	No	No	No
Mean control group	9.02	8.72	9.23	139
N	1885	837	1048	714
Partial F-Statistic	21.75	35.25	20.52	50.63
R-squared	0.110	0.156	0.115	0.134

Note: LATE results. Robust standard errors clustered at household level are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$. The period for the outcome variable is November 2019 to May 2020.

We find a statistically significant impact of house screening on labor supply. We estimate that screening reduces the number of workdays lost due to malaria by 1.82 days per adult. When aggregated to the household level (including adult children that work), house screening increases average labor supply during the peak season by 4.6 days. While this may be economically meaningful—see below—it is worth recalling that the total number of days away from work due to malaria (i.e., due to

Table 5
House screening and the number of malaria episodes (2SLS Regression).

	Full sample	Children (≤13 yrs)	Adults (>13 yrs)	Adult males	Adult females
House screening	−0.347**	−0.303	−0.409***	−0.401*	−0.384*
	(0.175)	(0.211)	(0.181)	(0.223)	(0.219)
95% Conf. Interval	−0.69 to −0.004	−0.72 to 0.11	−0.76 to −0.05	−0.84 to 0.04	−0.81 to 0.05
Constant	0.635**	0.486**	0.767**	0.800**	0.721
	(0.310)	(0.276)	(0.360)	(0.373)	(0.490)
Co-variates	No	No	No	No	No
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Mean control group	1.98	2.09	1.87	1.85	1.89
N	3703	1818	1885	837	1048
Partial F-Statistic	23.58	20.86	21.75	35.25	20.52
R-squared	0.119	0.159	0.124	0.177	0.141

Note: LATE results. Robust standard errors clustered at household level are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$, The period for the outcome variable is November 2019 to May 2020.

illness and care provision) at the household level stands at 36 days during the peak season. Stated otherwise, while HS reduces work absenteeism due to malaria, there is scope for additional measures to further increase labor supply—even after screening houses.

We find differences between male and female household members. While HS has a small and insignificant impact on male labor supply, we document a large and statistically significant effect for female household members. The average number of extra workdays for female household members due to HS is 2.56 days. This gender gap likely reflects differences in care provision responsibilities. Female household members were much more likely to stay at home when relatives are sick—caregivers are predominantly women. A large part of the impact of HS on the female labor supply reflects a reduced care burden for family members.

4.4. House screening and income

The impact of HS on our survey-based measure of household income is summarized in column 4 of Table 6. Expressed as a share of monetary income, HS increases per capita income by 39.6%. This amounts to a US $55 income gain per household.

This directly measured outcome can be compared to an indirect income estimate based on extra labor supply. We compute the income effect by multiplying extra working days per household by the daily wage rate. District-level wages were estimated from data obtained from a nationally representative agricultural livelihood survey, capturing agricultural and non-agricultural wage data across all districts of Zambia (but not capturing seasonal variation, unfortunately). Note that the Rural Agricultural Livelihood Survey (RALS) was carried in all districts of Zambia covering period May 2018 to March 2019 by the Indaba Agricultural Policy Research Institute and includes the slack agricultural season when casual wages tend to be lower. We selected Nyimba District to estimate mean wage rates for all possible labor activities that households in the study area are likely to engage in. The average mean wage equals US$5.94 per day, which is our proxy for the opportunity cost of labor. Based on additional labor valued at this price, we estimate an income gain per household of US$27 (or 4.6 × US$5.94).

This outcome is much lower than our direct income measure, which is not surprising. It reflects that, for land-owning families, the return to working on their own farm *during the growing season* exceeds the average off-farm return to casual labor. In other words, the average wage rate underestimates the true opportunity cost of time for farmers during the main growing season. This must be true, else many household members would be working off-farm during the peak season (which they do not do). Wages represent a lower bound for losses from a day of missed work due to illness, that could be much larger than the wage per day.

5. Costs and benefits of house screening

During the implementation of the experiment, we carefully kept track of all construction costs—material inputs, labor, and transport. Our estimate of the "full cost" of house screening per household equals $84.28. We assume the expected lifetime of the screens is equal to 4 years (Kirby et al., 2009). The cost of screening materials accounted for 80% of these total costs, and labor and transportation costs amounted to 11% and 7%, respectively. In addition to construction costs, there may be annual maintenance costs, which we estimate to be 5% per year of the construction costs. Our estimate is within the range of other cost estimates in the literature, but higher than most others. Our per capita screening cost is approximately US$19. Kirby et al. (2009) estimate per capita cost of $11.1 in Gambia and Getawen et al. (2018) estimate a cost of $6.5 for Ethiopia.

We use both our measures of the income gains due to providing house screens for households—the (direct) survey-based estimate and the (indirect) labor supply-based estimate. We compare costs of house screening with these economic benefits and compute the NPV for the entire 4-year period. Table 7 shows our estimates of the NPV for different assumptions with respect to discount rates and maintenance cost. Regardless of how we measure the gain in household income, the NPVs are consistently positive across discount rates and maintenance costs. This suggests providing house screening is a cost-effective intervention, increasing social welfare. The NPV based on the direct income measure is $118, and the NPV based on labor supply estimates amounts to $16. These estimates are fairly robust across scenarios, but it is clear from Table 7 that the NPV is small when we consider the combination of a high discount rate ($r = 10\%$) and income estimates based on labor supply.

Capital markets in rural Zambia are imperfect, and many households cannot borrow at an interest rate of 10% per year—informal money lenders and microfinance organizations typically charge rates much higher than that. For these households, therefore, the NPV of private benefits from house screens will likely be negative. The provision of publicly funded (or aid-funded) subsidies to reduce up-front investment costs may therefore be a welfare-enhancing policy.

It is important to emphasize that our estimates of the welfare effects of screening are likely underestimates or lower bounds of the true welfare gain. Several economic benefits of screening are not included in our analysis. Utility losses due to morbidity or mortality are not included, and neither is the decrease in health-related expenditures—the cost of medicines, hospitalization, transportation, among others. Moreover, the decline in the malaria burden frees up time for leisure and other activities, improving the overall welfare of households. Extra domestic work in the home goes unpaid and is difficult to value in economic terms, but valuable nonetheless. This reinforces the main insight that providing house screens is a welfare-enhancing strategy in rural Zambia. When rolled out at scale, there may be general equilibrium effects—lowering wages and raising prices of screening. It is an empirical question whether these effects dominate the partial equilibrium gains identified in this study.

6. Conclusions and discussion

We studied the economic impacts of malaria control through house screening (HS)—a complementary approach for limiting exposure to malaria vectors. The analysis is based on an RCT with two experimental arms: a treated group receiving HS plus LLIN and a control group receiving LLIN only. We report the economic impacts of house screening for the sub-sample of households living in houses that can be screened.

Our findings demonstrate that HS reduces malaria transmission with significant impacts on the self-reported prevalence of malaria, the number of malaria "sick days" and the number of malaria episodes. The HS intervention had significant economic effects, and that investing in house screening pays off in the sense that discounted benefits likely exceed costs. Therefore, investment in HS is privately optimal. If prospective buyers would be aware of these benefits and could access capital markets to finance the sizable up-front investment, then house screening may take off as a private protection strategy. However, capital

Table 7
Net present values for labor supply and income gains.

Discount rate (%)	Maintenance costs (%)	NPV labor supply gains (US$)	NPV income gains (US$)
3	5	15.98	117.98
10	5	2.99	91.77
3	0	19.93	121.92
10	0	6.42	95.20
3	3	17.56	119.56
10	3	4.36	93.14

Notes: Labor supply gains were computed based on the assumption that 2/3 of the working adults earn a high wage rate (above the mean), while 1/3 earn a low wage rate (below the mean). An expected wage rate was computed as $5.941 per day using the RALS dataset.

markets in rural Zambia are imperfect, and most households will be unable to obtain a loan to finance screening. Our partial equilibrium analysis suggests that public intervention to subsidize screening is likely welfare-enhancing.

While HS intends to protect all members in a household equally, we observe heterogeneity in the impact of screening for different household members. Specifically, the health impact on children is smaller than on adults. We provide data supporting the hypothesis that behavioral responses drive this heterogeneity. Children spent less time indoors after HS, while there was no discernible behavioral change in adults. We also find that women experience larger labor supply effects than men. A plausible explanation is that the overall decline in the malaria burden due to HS eases the burden for women to provide care to sick family members. In other words, the impact of house screening for individuals (a household-level public good) is mediated by behavior and gender roles. This insight is reinforced by the following. While we document a sizable impact of house screening, house screening does not provide full protection against malaria transmission. Perhaps this is because people get bitten by mosquitos elsewhere, or because most households do not have the discipline to behave consistently in accordance with instructions—to close windows and doors between dusk and dawn, and regularly inspect the screens and make repairs where needed. House screening alone is unlikely to eradicate malaria.

The finding that a sizable share of the households has houses in such a poor state that they cannot be included in the intervention has obvious implications for inter-household equity. These houses require substantial upgrades before they can be targeted for HS. It is an open question whether the benefits of screening will also dominate the cost if the additional investment costs associated with house upgrading are taken into account.

The study is certainly not without limitations. An important limitation is the use of self-reported malaria prevalence data, which can be an imprecise indicator even if assessed by health personnel. This is particularly true in the context of non-pharmacological interventions as households receiving the intervention might feel "more protected" and therefore may be less likely to report malaria. As mentioned, we rely on self-reported data because of budgetary implications and other constraints such the practicality of conducting several malaria tests over the entire study population over a period of 6 months. Another limitation of the study is non-compliance during implementation as house screening is not a suitable intervention for all households. Future RCTs on house screening should be based on better tailored sample frames, including only "screenable houses". Finally, house screening may improve the health of household members by reducing entry of other disease carrying insects such as flies, which may cause diarrhea. Since we did not collect any data on this, we may underestimate the full health impact of screening.

Credit author statement

Brian Chisanga: Conceptualisation, data collection, Formal analysis, writing Erwin Bulte: conceptualising, writing, review, editing Menale Kassie: conceptualising, writing, review, editing Clifford Mutero: Conceptualisation, review, editing Freddie Masaninga: Conceptualisation, Project administration Onyango Peter Sangoro: Conceptualisation, review, editing.

Ethical approval

Ethical approval was obtained from the Ethical Review Board, ERES Coverge IRB (Ref: 28-October-007).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A1

Table A1
House screening and malaria prevalence: First stage regressions

	Full sample	Children (≤13 yrs)	Adults (>13 yrs)	Adult males	Adult females
Treatment assignment	0.328***	0.337***	0.326***	0.301***	0.345***
	(0.038)	(0.040)	(0.038)	(0.046)	(0.039)
Constant	0.073	0.014	0.107	0.137	0.077
	(0.154)	(0.146)	(0.149)	(0.166)	(0.190)
Co-variates	No	No	No	No	No
Village F.E.	Yes	Yes	Yes	Yes	Yes
N	3703	1818	1797	789	1008
Partial F-Statistic	23.58	20.86	20.95	33.86	19.66
R-squared	0.224	0.210	0.212	0.195	0.186

Note: Robust standard errors in parentheses. Asterisks indicate the following: *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$. The dependent variable in this first stage regression is actual receipt of HS treatment ($d = 1$ if household received treatment and $d = 0$ otherwise). Treatment assignment, $z = 1$ if household was assigned to treatment, and $z = 0$ if otherwise.

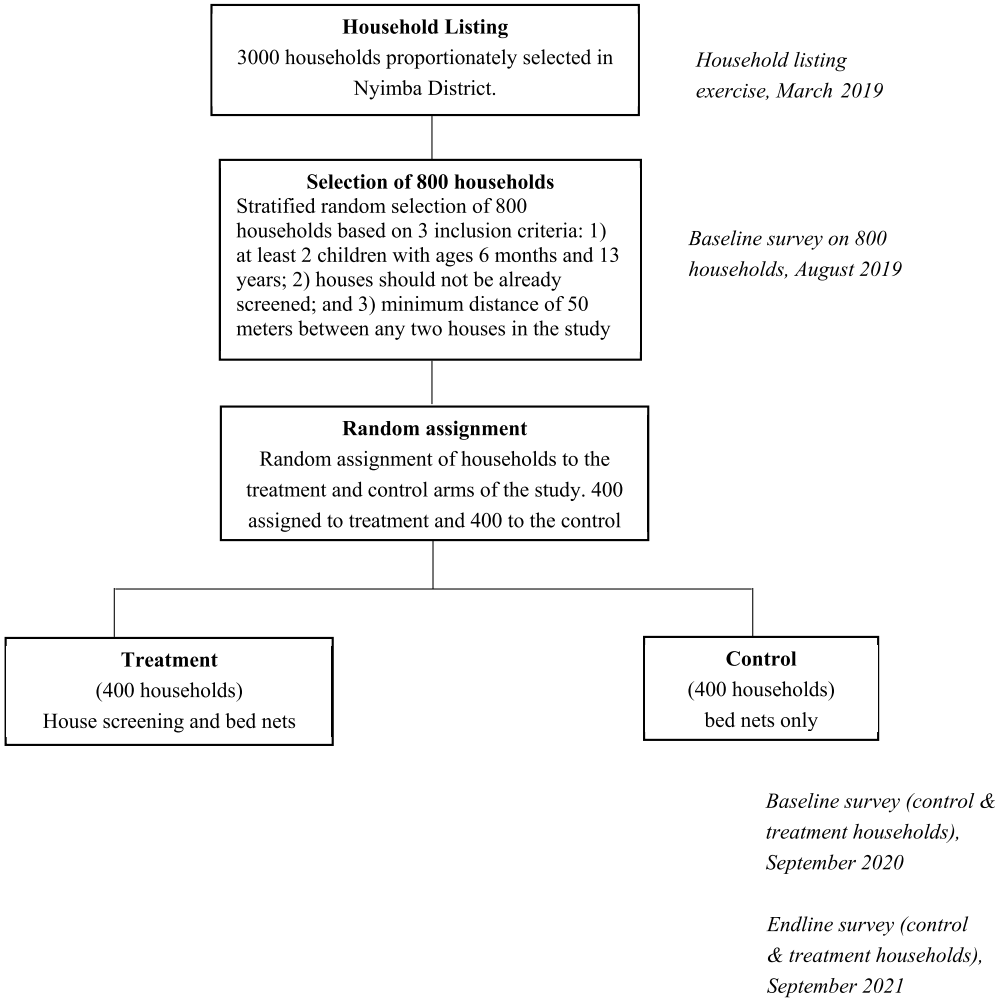
Table A2
Robustness check: Effect of 100m and 200m threshold on the HS effect size

	Distance threshold = 100 m	Distance threshold = 200 m
House screening	−0.229*	−0.224**
	(0.117)	(0.108)
95% Conf. Interval	−0.46 to 0.00	−0.44 to −0.01
Constant	0.235***	0.446***
	(0.0878)	(0.130)
Village FE	Yes	Yes
Covariates	No	No
Observations	1576	1416
R-squared	0.133	0.191

Note: LATE results. Robust standard errors clustered at household level in parentheses. Asterisks indicate the following: *$p < 0.1$, **$p < 0.05$, ***$p < 0.001$.

Appendix B
Materials used for the Participant Houses included in the Study

	Materials	Note
1.	Wire mesh as screening material	Used to screen windows and doors
2.	Wood (timber)	For the door and window frames
3.	Cement and sand	For sealing off openings
4	Accessories: wire nails, soft wire, door hinges	–



Appendix C. Sampling plan and RCT implementation

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