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Original Article

Does improving appropriate use of malaria medicines change population beliefs in testing and treatment? Evidence from a randomized controlled trial

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Abstract

A major puzzle in malaria treatment remains the dual problem of underuse and overuse of malaria medications, which deplete scarce public resources used for subsidies and lead to drug resistance. One explanation is that health behaviour, especially in the context of incomplete information, could be driven by beliefs, pivotal to the success of health interventions. The objective of this study is to investigate how population beliefs change in response to an experimental intervention which was shown to improve access to rapid diagnostic testing (RDT) through community health workers (CHWs) and to increase appropriate use of anti-malaria medications. By collecting data on individuals' beliefs on malaria testing and treatment 12 and 18 months after the experimental intervention started, we find that the intervention increases the belief that a negative test result is correct, and the belief that the first-line anti-malaria drugs (artemisinin-based combination therapies or ACTs) are effective. Using mediation analysis, we also explore some possible mechanisms through which the changes happen. We find that the experience and knowledge about RDT and experience with CHWs explain 62.4% of the relationship between the intervention and the belief that a negative test result is correct. Similarly, the targeted use of ACTs and taking the correct dose—in addition to experience with RDT—explain 96.8% of the relationship between the intervention and the belief that the ACT taken is effective. As beliefs are important determinants of economic behaviour and might guide individuals' future decisions, understanding how they change after a health intervention has important implications for long-term changes in population behaviour.

Keywords: Malaria, ACTs, beliefs, rapid diagnostic testing

Introduction

A major puzzle in malaria treatment is the dual problem of underuse and overuse of malaria medication. The inappropriate use of malaria medication includes patients who test malaria-positive, but do not take the most effective class of anti-malaria drugs—artemisinin-based combination therapies (ACTs), as well as consumption of ACT by patients who do not have malaria, which is often exacerbated by deep subsidies for the drug (Briggs *et al.*, 2014; Cohen *et al.*, 2015). In malaria-endemic countries, non-malaria febrile

Key Messages

- Little is known about the role and the evolution of beliefs in the context of malaria.
- We investigate how population beliefs change in response to an experimental intervention that improves access to testing and increases appropriate use of antimalarial medications.
- We find that intervention increases the belief that a negative test result is correct and the belief that the first-line antimalarial drugs are effective.
- Using mediation analysis, we explore the mechanisms and we confirm that the changes in beliefs are due to behaviour changes caused by the experimental intervention.

illnesses are common and they are frequently treated at retail drug stores. Fewer than 15% of potential malaria cases receive appropriate therapy (WHO, 2012). In our setting, rural Western Kenya, malaria testing is relatively uncommon with 43% of individuals reporting being malaria tested for their recent febrile illness. More than 70% of individuals with a recent fever reported taking ACT, nearly two-thirds of which was sourced from the retail sector: although 84% of those testing positive reported taking ACT, 60% of those not tested for malaria and 34% of those who tested negative also took ACT (Prudhomme O'Meara *et al.*, 2018). This inappropriate testing and treatment behaviour contribute to the global burden of disease, by depleting scares public resources used for subsidies, and by potentially increasing the risk of pathogen resistance to ACT (Laxminarayan, 2004; Lin *et al.*, 2010; WHO, 2012).

One potential explanation for individuals' inappropriate testing and treatment is that health behaviour, especially in the context of incomplete information, could be driven by beliefs—broadly defined as individuals' self-assessment of the likelihood of an uncertain event. These include people's beliefs about their illness being malaria, the diagnostic test being correct and drugs being effective. Often, people have to make decisions about their health with incomplete information, relying on their beliefs instead. There is a growing literature in education (Attanasio and Kauffman, 2009; Jensen, 2010; Arcidiacono *et al.*, 2012; Zafar, 2013), migration (McKenzie *et al.*, 2013), financial and labour markets (van der Klaauw and Wolpin, 2008; Chetty and Saez, 2013; Delavande and Rohwedder, 2011; Kezdi and Willis, 2009) that studies the role of beliefs in economic behaviour. Previous research on beliefs in the context of health has shown the importance of beliefs for fertility choices (Shapira, 2013), contraceptive behaviour (Delavande, 2008) and risky behaviour in the context of HIV and addictions (Cawley and Ruhm, 2011; Gerking and Khaddaria, 2012; Winter and Wuppermann, 2014; Delavande and Kohler, 2016). A few studies, such as Dupas (2011), focus on how information interventions change beliefs and behaviour in the context of HIV testing and sexual behaviour. However, there is relatively little research that investigates the role of beliefs in healthcare choices in the context of malaria, even though the disease has a large global morbidity and mortality burden (Adhvaryu, 2014; Maffioli *et al.*, 2019).

In the context of malaria testing and treatment, there is little quantitative evidence on the relationship between behaviour and beliefs. Several qualitative studies suggest the importance of beliefs in malaria-related health behaviour related to drug purchases (Metta *et al.*, 2014), and acceptability of rapid diagnostic test or trust in test results (Comoé *et al* 2012; O'Neill *et al.*, 2015). Maffioli *et al.* (2019) explore the relationship between prior beliefs on malaria status and the decisions to get tested and purchase ACT. The authors find that price changes as a result of large experimental subsidies were a stronger driver of behaviour in this context than people's beliefs about testing and treatment. However, it remains unclear to what extent beliefs are malleable and how they could change following population interventions. In fact, little is known about how health beliefs might evolve over time in response to population-level interventions that introduce new technologies that can better detect and treat illnesses. More broadly, understanding how the experiences of care affect beliefs is important to inform the provision of care in low-income countries: understanding whether beliefs could explain low take-up of health interventions even when they are widely available and subsidized (Ashraf *et al.*, 2010; Cohen and Dupas, 2010) might shed some light on the role that beliefs play in individuals' decision to seek care. As drivers of individual behaviour, beliefs are central to the development of effective population interventions. The take-up and success of these interventions are sustained by the evolution of individual beliefs, which might speed up learning and increase returns to innovations (Adhvaryu, 2014; Dupas, 2014).

In this article, we first exploit a community-based cluster-randomized controlled trial in rural Kenya to explore how improvements in access to malaria diagnostic testing and to ACTs affect people's beliefs about their malaria status, about the results of diagnostic testing and about the drug taken. The experimental intervention provided rapid diagnostic testing (RDT) through community health workers (CHWs), and ACTs subsidies (conditional on a positive test) to a randomly selected sample of 32 communities in Western Kenya. The goal was to improve testing take-up and adherence to the test result. Second, since this was a complex intervention (Medical Research Council, 2000) that had impacts on multiple behaviours, we also attempt to identify which behavioural changes had the largest effect on beliefs. We in fact explore some mechanisms through which our population-level experimental intervention affected beliefs, by investigating which of the testing and treatment behaviours modified by the intervention, might play a major role in explaining any changes in population beliefs.

Background and setting

Our study exploits a large cluster-randomized controlled trial conducted in 32 community units (CU) in three sub-counties—Webuye West, Webuye East and Kiminini—in western Kenya, covering about 160 000 people, which had the goal to improve testing take-up as well as appropriate use of ACTs for those in need. Each sub-county is divided in administrative units of about 1000 households (CUs), and each CHW is responsible for 45–100 households. Ten CUs in Webuye East, 8 CUs in Webuye West and 14 CUs in Kiminini had active and pre-existing CHWs and were eligible to participate in the study. We randomized at the level of CUs. We divided

CUs into five strata based on sub-county and whether a public health facility that offered malaria diagnostic testing was located within the sub-county. Within each stratum, we then randomly assigned half of the CUs to treatment and half of the CUs to control [see Figure 2, CONSORT diagram in Prudhomme O'Meara *et al.* (2018)].

In the intervention group, CHWs were trained to perform malaria RDTs and to offer free testing to residents. Any child (older than 1 year) or adult person who had a fever or malaria-like symptoms in the previous 48 h could request a free RDT from the CHW. If the RDT showed a positive result, CHWs offered a voucher for discounted ACTs. The residents could redeem the voucher, within 2 days of testing, to any local retail shop enrolled in the study which had quality-assured artemether lumefantrine (AL; i.e. the first-line ACT recommended for uncomplicated malaria by the Government of Kenya). The intervention was sensitized through meetings with community leaders, appearances at public meetings and printed posters in retail outlets. In the control group, sick residents could visit government or private health facilities, or self-treat at pharmacies or retail medicine outlets. CHWs, who are unpaid volunteers, continued to provide health education, disease prevention and referral services, following the Kenya's Community Strategy plan (Ministry of Health, Kenya, 2006).

Prudhomme O'Meara *et al.* (2018) find large increases in malaria testing rates in intervention compared with control areas at 12 months (adjusted risk ratio [ARR] = 1.20; 95% CI 1.05–1.38; $P = 0.015$) and 18 months (ARR = 1.25; 95% CI 1.09–1.44; $P = 0.005$). Furthermore, there was an increase in appropriate consumption of ACTs, defined either as targeted use (positives taking ACT or negatives not taking ACT, evaluated among all fevers, ARR 1.46; 95% CI 1.20–1.79; $P < 0.001$) or rational use (the per cent of all ACTs used that were taken by people with a positive malaria test, evaluated among ACT users, ARR 1.40; 95% CI 1.19–1.64; $P < 0.001$).

Methods

Data

The data used in the analysis were collected as part of the randomized intervention described in Prudhomme O'Meara *et al.* (2018), which was launched between July and August 2015. Household and individual data were collected in repeated cross-sectional surveys at four time points: baseline (conducted between February and April 2015), 6, 12 and 18 months post-baseline (the final survey was planned for 18 months post-baseline, but a nationwide doctor's strike forced a 2-month delay), targeting any household who had at least one member (older than 1 year) who had fever or malaria-like symptoms in the past month. For details on power and sample size of the overall study see Laktabai *et al.* (2017).

Our sample includes over 5800 individuals: 2066 individuals at baseline, 1660 at 6 months, 1812 at 12 months and 1927 at 18 months. The surveys collected socio-demographic data on the patient and the household, treatment and test-seeking behaviour, drug consumption as well as data on beliefs, as individuals' self-assessment of the likelihood of an uncertain event. We use a five-point Likert scale from 'very unlikely' to 'very likely' to ask the respondents about the likelihood that their fever (or the fever of the child) in the past month was malaria, and the likelihood that a malaria test result is correct if a hypothetical febrile patient tests positive, or if a hypothetical febrile patient tests negative. In addition, if individuals took a drug for their fever, respondents were asked about the likelihood that the drug they took was effective in treating their illness. Individuals who took AL were asked about the effectiveness of AL in treating malaria. All these beliefs data were collected at baseline, 12 and 18 months. The 18-month wave of data also includes information on respondents' beliefs about the veracity of their own malaria test results, and beliefs about whether a hypothetical individual who definitely has malaria would recover in 3 days with AL treatment. If the patient with fever or malaria-like symptoms in the past month was a child (<18 years), the parent or guardian provided information on beliefs for the child.

Empirical analysis

Our goal is to test whether the experimental intervention had any effect on population beliefs about malaria status, test results and drug effectiveness. We compare beliefs at 12 and 18 months (or pooled) between treatment and control group. Since, in our setting, the most common response to the beliefs question is 'very likely' (frequently >50% of the responses, see Table 1), we analyse our primary outcomes of interest (belief) as a discrete variable, comparing 'very likely' vs 'very unlikely', 'unlikely', '50–50', 'likely'. We also conduct sensitivity analyses with two other potential specifications for the outcome: (i) grouping 'likely' and 'very likely' together, and comparing it to '50–50', 'unlikely', 'very unlikely' and (ii) a multinomial logit specification by combining the smallest categories ('unlikely', 'very unlikely') together. The main estimates remain robust to both specifications (Supplementary Tables SA2 and SA3).

We look at three types of beliefs: beliefs about malaria status, beliefs about the diagnostic test being correct and beliefs about the effectiveness of the drug taken (ACT or other drugs). We estimate an intention-to-treat effect, through a standard logit model specification as follows:

$$\Pr(y = 1/\mathbf{X}) = \Lambda(\alpha + \beta\ \text{Treatment} + \gamma\ \mathbf{X} + \mathbf{s} + \varepsilon)$$

where y is our outcome of interest, expressed as an indicator equal to 1 if the respondent very likely believed in an event and equal to 0 otherwise. Treatment is expressed as an indicator equal to 1 if the CU where the respondent lives were assigned to the intervention arm and equal to 0 if it was assigned to the control group. The model includes five strata fixed effects (**s**) to account for the stratified design. The strata are defined by interacting three indicators for the sub-counties (Bokoli, Kimini and Ndivisi), and two indicators for whether the sub-county includes a health facility or not. However, one sub-county (Bokoli) does not have a facility, so in practice we include five strata indicators. ε is a normally distributed random error term with mean of zero. We also include additional covariates (**X**): age (1–4, 5–17 and 18+ years), sex, education level of the respondent and household wealth index quintile (see Supplementary Table S1 in Prudhomme O'Meara *et al.*, 2018). The target sample size of eligible individuals with a fever in the last 4 weeks was estimated to be 640 per arm (i.e. 40 per CU) at each time point [see Laktabai *et al.* (2017) for details on sample size calculations of the experimental intervention]. Since we designed our study to equally weight each CU in the analysis by sampling the same number of fevers per CU (i.e. 40), we computed survey weights = (N_k, total/32)/N_ik, such that $i = 1,\ldots 32$ indicates CU; $k = 0$, 1, 2 and 3 indicates baseline, 6, 12 and 18 months post-baseline, respectively; N_k, total represents the total number of fevers surveyed across all CUs at time point k; and N_ik represents the actual number of fevers in CU i at time point k (Prudhomme O'Meara *et al.*, 2018). The regressions are thus adjusted including these weights to account for the unequal numbers that were obtained in practice due

Table 1 Summary statistics on beliefs (all available waves)

Beliefs about	Malaria	Test			Drug		
	Illness Malaria	Negative test correct	Positive test correct	Own test correct	Drugs taken effective	AL taken effective	Recover 3d with AL
Very likely	53.79	35.59	79.61	65.55	61.16	64.47	41.58
Likely	31.47	25.92	18.26	29.49	29.79	28.06	37.86
50–50	11.55	11.22	1.49	2.80	5.67	4.76	10.45
Unlikely	2.28	11.95	0.22	1.51	2.47	1.89	8.21
Very unlikely	0.91	15.31	0.42	0.65	0.92	0.82	1.91
Observations	7063	4895	4968	929	4660	4030	1828
Waves	All waves	Bas-12m-18m	Bas-12m-18m	18m	Bas-12m-18m	Bas-12m-18m	18m

This table presents summary statistics of beliefs in all available waves (baseline, 12, 18 months). Means (%) are reported. The variables refer to the likelihood that the illness is malaria; the likelihood that a malaria negative test is correct; the likelihood that a malaria-positive test is correct; the likelihood that the malaria test taken is correct (among those who took a malaria test); the likelihood that the drugs taken are effective; the likelihood that AL taken is effective; and the likelihood that if the respondent takes AL in the hypothetical scenario she has malaria, she would recover in 3 days.

Bas-12m-18m, baseline, 12, 18 months.

to the systematic random sampling approach used. We report odds ratios from this estimation. Standard errors are clustered at CU level.

Our study also attempts to understand some of the factors that contribute to the changes in population beliefs after the experimental intervention. Our hypothesis is that, since the intervention affected health-seeking behaviour (shown in Prudhomme O'Meara *et al.*, 2018), these changes in behaviour might affect population beliefs. Thus, we conducted a mediation analysis (Judd and Kenny, 1981; MacKinnon *et al.*, 2007) to explore the role of potential mediating factors. We define mediators as those factors which speak to how and why an effect occurs (Baron and Kenny, 1986). More precisely, we are interested in learning about which mediating factors explain the effect of the experimental intervention [A] on population beliefs [Y]. We primarily consider as mediators [M] testing and treatment behaviours that were changed by the experimental intervention. The intervention caused a higher take-up of malaria testing (Prudhomme O'Meara *et al.*, 2018), leading to a higher proportion of population who had experience with malaria testing, and specifically RDTs provided by CHWs. In addition, the intervention caused an increase in the targeted use of AL, leading to a higher proportion of individuals testing positive who took AL and testing negative who did not take AL, among all fevers. Population beliefs could then be affected by the individuals learning from their experience with recovery after testing and treatment.

As Figure 1 shows, we consider several variables related to testing and treatment behaviour for the mediation analysis. Since more individuals in the treatment group received malaria testing—specifically RDT through CHWs—compared with the control group, we consider the following six mediating factors for testing behaviour: (1) the experience with the test: whether the individual ever had a malaria test; whether the individual ever had an RDT; (2) the experience with CHW: whether a CHW is present in the village; whether the individual ever contacted the CHW for an illness; (3) the knowledge about RDT: whether the individual knows what RDT is; whether the individual ever had an RDT or knew someone who had it. In addition, since more individuals in the treatment group, compared with the control group, received a subsidy for AL after deciding to be tested and knew their (positive) malaria status, consequently (potentially) taking the appropriate drug and recovering, we consider the following five mediating factors for treatment behaviour: (1) the experience with test: whether the individual ever had a malaria test; whether the individual ever had an RDT; (2) the malaria status: whether the individual's test result was negative (vs positive); (3) the appropriate use of AL: whether the individual tested positive took AL or tested negative did not took AL (targeted use); whether the individual who took AL took the correct dose.

Since the experimental intervention changed both testing and treatment behaviour [M], these mediators could be influenced by the intervention and also affect beliefs. Thus, the changes in beliefs that we observe as researchers might be, at least partially, explained by these mediators. When a mediator is hypothesized, the total effect can be broken down into two parts: a direct effect and an indirect effect. The direct effect is the effect of the intervention on beliefs absent the mediator. The indirect pathway is the effect of the intervention on beliefs that works through the mediator(s). The results report odds ratios from a logit empirical model of the total, direct and indirect effect. The empirical analysis also estimates the proportion (%) of the total effect that comes from the indirect effect (through the mediators), i.e. the relative contribution of the indirect effect to the total effect for each mediator considered in the analysis (more details in the Results section). We chose a mediation analysis which allows for multiple mediators, mediators following any distribution, and for A-M interaction (Buis, 2010), to understand how much these mediating factors (M) contribute to explaining the relationship between the intervention and population beliefs (A and Y). Overall, the goal is to develop a better understanding about which behaviours (changed by the experimental intervention) might explain the changes in population beliefs.

Results

Table 1 presents summary statistics on the beliefs data collected across waves. Over the study period (across all time periods), 53.79% of the respondents very likely believed that their fever was malaria, only 35.59% of them very likely believed in a negative test result, while 79.61% of them very likely believed in a positive test result. About 65.55% of the respondents very likely believed in the result of their own malaria test. Among drug takers, 61.16% very likely believed that the drug they took was effective. Among AL takers, 64.47% very likely believed that the AL they took was effective in treating their fever. 41.58% also very likely believed that a person with malaria would recover in 3 days if AL was taken.

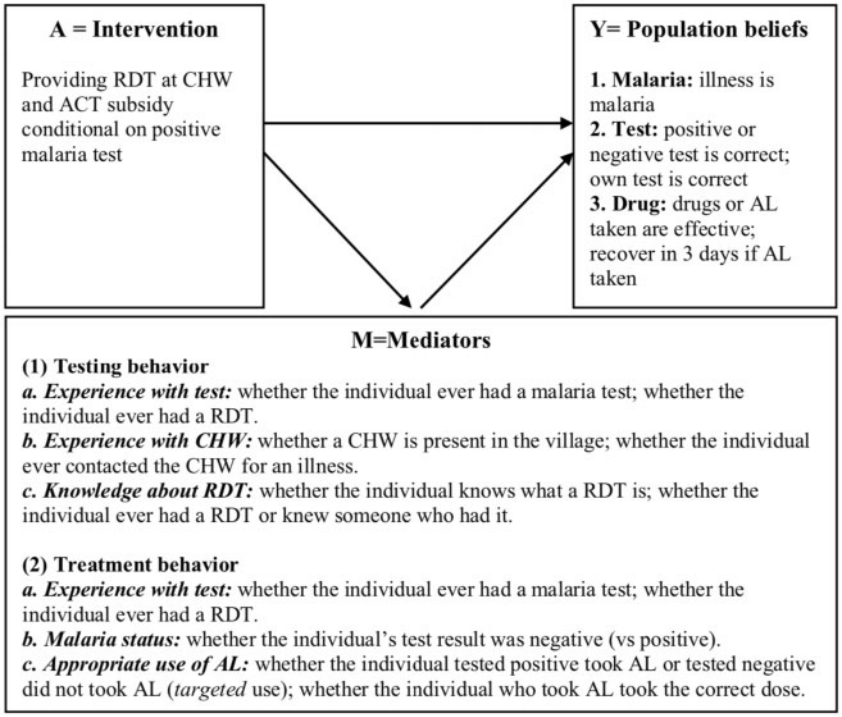

Figure 1 Mediation analysis.

Supplementary Table SA1 presents summary statistics on beliefs at baseline, by treatment status.

Beliefs

The effect of the intervention on beliefs

Table 2 describes the effect of the intervention on population beliefs, by wave. Estimates show that the intervention increased the odds that individuals very likely believed that a negative test was correct (odds ratio [OR] = 1.405, $P < 0.01$) and that the AL taken was effective in curing malaria (OR = 1.248, $P < 0.1$) after 12 months (Panel A, columns 2 and 6). At 18 months (Panel B, columns 5 and 6), the intervention also increased the odds that individuals very likely believed that any drug taken or AL taken was effective in curing malaria (OR = 1.225, $P < 0.10$, and OR = 1.279, $P < 0.05$, respectively). Results are similar, but more precise when pooling the two waves at 12 and 18 months (Panel C). We find increases in the odds that individuals very likely believed that a negative test was correct (OR = 1.300, $P < 0.05$, column 2), and that any drug taken (OR = 1.154, $P < 0.1$) or AL taken (OR = 1.295, $P < 0.01$) was effective in curing malaria. The result on the belief that a negative test result is correct appears to not be driven by a single type of individual, i.e. those who tested negative, positive or without test (Supplementary Table SA4, Panel C, columns 2, 7, 12), while the results on AL effectiveness are driven by individuals (AL takers) who were tested (Supplementary Table SA4, Panel C, columns 5 and 10). The results on any drug effectiveness are driven primarily by individuals tested positive (Supplementary Table SA4, Panel C, column 4). We do not find statistically significant differences at the 10% level for the other beliefs explored.

Mediation analysis

For the mediation analysis, we first establish how the experimental intervention affects the potential mediators (Figure 1, A→M). We then select the primary mediators that are influenced by the intervention. Finally, we perform the mediation analysis on these selected factors, estimating the direct and indirect effect and providing quantitative evidence on how much of the relationship between the intervention and beliefs is explained by these mediators. We do this separately for two main outcomes that the intervention changed (Table 2): (1) the belief that a negative test result is correct (column 2) and (2) the belief that AL taken is effective in curing malaria (among AL takers) (column 6).

Mediators of the belief that a negative test is correct

We find a statistically significant effect of the experimental intervention on the belief that a negative test result is correct at 12 months and in the pooled sample (Table 2, column 2). We know that the intervention led to higher take-up of malaria testing (Prudhomme O'Meara *et al.*, 2018). This implies that, after the intervention, there was a higher proportion of population who had experience with malaria testing, and specifically RDTs provided by CHWs. Consequently, these individuals might have better information about a test being correct, given their individual experience with recovery.

Thus, when studying the effect of the experimental intervention on the population belief that a negative test is correct (Table 3), we consider the following mediators to potentially play an important role (Figure 1): (1) the experience with malaria testing, namely test take-up (column 1) and personal experience with RDT (column 2); (2) the interaction with CHW, namely whether a CHW is present in the village (column 3) and whether the individuals ever contacted the CHW for an illness (column 4); (3) the knowledge about the RDT, namely whether the individual knows what an RDT is (column 5) and whether she ever had an RDT or knew someone who had it (column 6). We find strong statistically significant effect of the intervention on all these potential mediators: respondents in the treatment group are more likely to have taken a malaria test (OR = 1.460, $P < 0.01$), to have ever had experience with an RDT

Table 2 The effect of the intervention on beliefs [Logit model (odds ratios)]

Beliefs about Dependent variable: population beliefs (very likely vs other)	(1) Malaria Illness Malaria	(2) Negative test correct	(3) Test Positive test correct	(4) Own test correct	(5) Drugs taken effective	(6) Drug AL taken effective	(7) Recover 3d with AL
Panel A: 12 month							
Treatment	1.021	1.405***	1.162		1.058	1.248*	
	(0.0634)	(0.182)	(0.248)		(0.115)	(0.166)	
Observations	1711	1661	1688		1723	1271	
Panel B: 18 month							
Treatment	1.159	1.210	1.065	1.132	1.225*	1.279**	1.041
	(0.125)	(0.195)	(0.194)	(0.170)	(0.135)	(0.135)	(0.137)
Observations	1849	1253	1276	924	1459	1388	1822
Panel C: Pooled							
Treatment	1.118	1.300**	1.149		1.154*	1.295***	
	(0.0802)	(0.133)	(0.169)		(0.0885)	(0.113)	
Observations	3560	2914	2964		3182	2659	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the effects of the intervention on population beliefs, by wave. The empirical model is a logit model weighted by survey weights. Odds ratios are reported. The variables are defined as 1 if the respondent answers 'very likely' and 0 otherwise ('very unlikely', 'unlikely', '50–50', 'likely') and refer to the likelihood that the illness is malaria; the likelihood that a malaria negative test is correct; the likelihood that a malaria-positive test is correct; the likelihood that the malaria test taken is correct (among those who took a malaria test); the likelihood that the drugs taken are effective; the likelihood that AL taken is effective; and the likelihood that if the respondent takes AL in the hypothetical scenario she has malaria, she would recover in 3 days. Controls include five strata fixed effects to account for the level of randomization, indicators for wealth quintile, patient age (<5, 5–17, 18+), female gender and highest level of education of the respondent (none or less than primary, completed primary, completed secondary). Pooled sample also includes a time indicator for 18 months. Standard errors are clustered at CU level. $^{*}P < 0.1$; $^{**}P < 0.05$; $^{***}P < 0.01$.

Table 3 The effect of intervention on potential mediators of the belief that a negative malaria test is correct

Mediators	(1) Experience with test	(2)	(3) Experience with CHW	(4)	(5) Knowledge about RDT	(6)
	Ever took test	Ever took RDT	CHW in village	CHW contacted	Know RDT	Heard RDT
Panel A: 12 month						
Treatment	1.362**	1.562**	1.637**	7.144***		
	(0.186)	(0.275)	(0.343)	(1.241)		
Observations	1733	1237	1626	1329		
Panel B: 18 month						
Treatment	1.542***	1.688***	2.136***	9.051***	4.116***	2.768***
	(0.209)	(0.209)	(0.450)	(1.638)	(0.714)	(0.746)
Observations	1893	1275	1770	1486	1907	1178
Panel C: Pooled						
Treatment	1.460***	1.634***	1.851***	8.216***		
	(0.163)	(0.191)	(0.291)	(1.042)		
Observations	3626	2512	3396	2815		
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the effect of the intervention on mediators of the belief that a negative test is correct, by wave. The empirical model is a logit model, weighted by survey weights. Odds ratios are reported. The variables are defined as whether the individual took a malaria test, whether the respondent ever took an RDT; whether the respondent knows if there is a CHW in her village that provides any services of health education; whether the respondent ever contacted a CHW near her for any illness (of herself or someone in the household); whether the respondent knows what an RDT is; and, whether the respondent ever had an RDT or knew someone who had an RDT. Controls include five strata fixed effects to account for the level of randomization, indicators for wealth quintile, patient age (<5, 5–17, 18+), female gender and highest level of education of the respondent (none or less than primary, completed primary, completed secondary). Pooled sample also includes a time indicator for 18 months. Standard errors are clustered at CU level. $^{*}P < 0.1$; $^{**}P < 0.05$; P < 0.01.

(OR = 1.634, $P < 0.01$), to know about the presence of a CHW in their villages (OR = 1.851, $P < 0.01$), and to have ever contacted a CHW (OR = 8.216, $P < 0.01$). At 18 months, respondents in the treatment group are also more likely to know what an RDT is (OR = 4.116, $P < 0.01$) or to have had or know someone who had an RDT (OR = 2.768, $P < 0.01$). The estimates suggest that all these factors might have contributed to an increase in the belief that a negative test result is correct after the experimental intervention.

Table 4 Mediation analysis of the effect of the intervention on the belief that a negative test is correct (pooled sample across waves)

	OR	Bootstrapped standard error	$P > \|z\|$	[95% confidence interval]	
Total effect	1.361	0.138	0.002***	1.115	1.659
Indirect effect	1.211	0.069	0.001***	1.084	1.354
Direct effect	1.123	0.130	0.315	0.896	1.408
% of indirect/total effect	0.624	0.419	0.136	−0.197	1.445
$N = 2035$					
Replications = 500					

This table presents the results from the mediation analysis of the effect of the intervention on the belief that a negative test is correct (pooled sample across waves). The estimates reported are odds ratios of the direct effect of the intervention on beliefs absent the mediators, and the indirect effect of the intervention on beliefs that works through the mediators. The comparison is between treatment ($i = 1$) and control ($j = 0$) groups. The indirect effect = Odds_*ij*/Odds_*jj* and the direct effect = Odds_*ii*/Odds_*ij*. The size of the indirect effect relative to the total effect is also shown. Standard errors are bootstrapped with 500 replications.
*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$.

Table 5 Relative contributions (%) of the indirect effect to the total effect, for the belief that a negative test is correct

% indirect of total effect of mediators	(1) Ever took test (%)	(2) Ever took RDT (%)	(3) CHW in village (%)	(4) CHW contacted (%)	(5) All mediators (%)
12 months	0.3	32.6	1.9	27.2	48.3
18 months	5.5	21.6	−19.5	61.2	78.3
Pooled waves	1.0	31.0	−1.0	42.6	62.4

This table presents the results from the mediation analysis of the effect of the intervention on the belief that a negative test is correct, by wave. The estimates reported are the relative contribution of the indirect effect of the intervention on beliefs that works through the mediators of the total effect, by each mediator and by wave. In cases in which the direct and indirect effects have opposite signs, we run into the so-called case of 'inconsistent mediation'. Inconsistent mediation models are models where at least one mediated effect has a different sign than other mediated or direct effects in a model (Blalock, 1969; Davis, 1985; MacKinnon *et al.*, 2000). In this case, the percentage of the indirect effect (proportion mediated), which explains the total effect can result in a number lower than 0% or bigger than 100%. The estimates in column (3) at 18 months and pooled waves are then not meaningful and should not be interpreted.

Table 4 presents results from the mediation analysis of the effect of the experimental intervention on the belief that a negative test is correct, considering the four mediators in Table 3, columns 1–4. The estimates are odds ratios of the direct effect of the intervention on beliefs absent the mediators, and the indirect effects of the intervention on beliefs that work through the mediators. The comparison is between treatment ($i = 1$) and control ($j = 0$) groups. We find that the odds of very likely believing that a negative test result is correct for respondents in the intervention group are 1.36 times as large as the odds for control group [total effect]. Respondents in the control group would have 1.21 times higher odds of very likely believing that a negative test result is correct if they had the same knowledge/behaviour (mediators) as the respondents in the intervention group [indirect effect]. Finally, respondents in the intervention group would have 1.12 times higher odds of very likely believing that a negative test result is correct than the respondents in the control group if the knowledge/behaviour (mediators) were kept constant at the level of respondents in the intervention group [direct effect]. Taking all the results together, the take-away is that the indirect effect of the intervention on beliefs that works through the mediators is about 62.4% of the total effect, suggesting that the mediators considered explain more than half of the changes we find in population beliefs.

Table 5 summarizes the size of the indirect effect relative to the total effect for the belief that a negative test is correct, across waves and by each mediator considered. Estimates show that the experience with an RDT (column 2) and whether respondents ever contacted a CHW (column 4) together explain most of the indirect effect. In addition, the indirect effect of the intervention on beliefs that works through the mediators is higher at 18 months compared with 12 months (78.3% vs 48.3% in column 5). Supplementary Table SA5 extends this analysis to the relative contributions of the other mediators considered at 18 months in Table 3, columns 5 and 6.

Mediators of the belief that AL is effective in curing malaria (among AL takers)

We also find a statistically significant effect of the experimental intervention on the belief that AL is effective, among those who took AL (Table 2, column 6). In addition to the main impacts of the intervention considered above, recall that, we find an increase in the targeted use of AL (at 12 and 18 months). This implies that the intervention leads to a higher proportion of individuals testing positive who took AL and testing negative who did not take AL, among all fevers, and thus they might have recovered better and learned from their experience with the recovery.

Thus, when studying the effects of the intervention on the population belief that AL was effective in curing malaria (Table 6), we consider the following mediators to potentially play an important role (Figure 1): (1) the experience with malaria testing, namely test take-up (column 1) and personal experience with RDT (column 2); (2) the individual malaria status, namely whether the status is negative (vs positive) (column 3); and (3) the appropriate use of AL, namely the targeted use of AL (column 5) and whether the correct dose of AL was taken (column 6). We find statistically significant evidence that respondents in the treatment group were more likely to have taken a malaria test (OR = 1.664, $P < 0.01$), to have ever had experience with an RDT (OR = 1.784, $P < 0.01$), to show targeted use of AL (OR = 1.670, $P < 0.01$) and to have taken the correct dose of AL (OR = 1.428, $P < 0.01$) (Panel C). At 12 months, AL takers in treatment group are also more likely to have a test result negative compared with control group (OR = 2.336, $P < 0.01$), but this might be due to selection into testing. The estimates confirm

Table 6 The effect of intervention on potential mediators of the belief that AL is effective in curing malaria (among AL takers)

Mediators:	(1)	(2)	(3)	(4)	(5)
	Experience with test		Malaria status	Appropriate use of AL	
	Ever took test	Ever took RDT	Test result negative	AL targeted	Correct dose
Panel A: 12 month					
Treatment	1.445**	1.681***	2.336***	1.273	1.330***
	(0.241)	(0.276)	(0.577)	(0.232)	(0.120)
Observations	1274	930	640	1254	1167
Panel B: 18 month					
Treatment	1.880***	1.898***	0.665	2.094***	1.450***
	(0.262)	(0.249)	(0.200)	(0.304)	(0.193)
Observations	1418	1006	794	1395	1385
Panel C: Pooled					
Treatment	1.664***	1.784***	1.229	1.670***	1.428***
	(0.212)	(0.188)	(0.272)	(0.223)	(0.116)
Observations	2692	1936	1434	2649	2552
Controls	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes

This table presents the effects of the intervention on mediators of the belief that AL is effective in curing malaria, by wave. The empirical model is a logit model weighted by survey weights. Odds ratios are reported. The variables are defined as whether the respondent ever took a malaria test, whether the respondent ever took an RDT, whether the test result was negative (vs positive), whether there is targeted AL use (positive, took AL; negative, did not take AL among all fevers); whether the respondent took the correct dose of AL. Controls include five strata fixed effects to account for the level of randomization, indicators for wealth quintile, patient age (<5, 5–17, 18+), female gender, and highest level of education of the respondent (none or less than primary, completed primary, completed secondary). Pooled sample also includes a time indicator for 18 months. Standard errors are clustered at CU level. $^{*}P<0.1$; $^{**}P<0.05$; $^{***}P<0.01$.

Table 7 Mediation analysis of the effect of the intervention on the belief that AL is effective in curing malaria (pooled sample across waves)

	OR	Bootstrapped standard error	$P>\|z\|$	[95% confidence interval]	
Total effect	1.171	0.119	0.119	0.960	1.429
Indirect effect	1.165	0.033	0.000***	1.104	1.231
Direct effect	1.005	0.102	0.960	0.824	1.231
% of indirect/total effect	0.96.8	7.204	0.893	−13.153	15.089
$N=1790$					
Replications = 500					

This table presents the results from the mediation analysis of the effect of the intervention on the belief that AL is effective in curing malaria (pooled sample across waves). The estimates reported are odds ratios of the direct effect of the intervention on beliefs absent the mediators, and the indirect effect of the intervention on beliefs that works through the mediators. The comparison is between treatment ($i=1$) and control ($j=0$) groups. The indirect effect = Odds_*ij*/Odds_*jj* and the direct effect = Odds_*ii*/Odds_*ij*. The size of the indirect effect relative to the total effect is also shown. Standard errors are bootstrapped with 500 replications. $^{*}P<0.1$; $^{**}P<0.05$; $^{***}P<0.01$.

that the majority of the factors considered might have contributed to an increase in the belief that AL was effective in curing malaria. Thus, we select the mediators which matter most (ever took a test, ever took an RDT, AL targeted use, correct AL dose, columns 1, 2, 4 and 5) to conduct the mediation analysis and investigate how much these factors contributed to the changes in population beliefs.

Table 7 presents results from the mediation analysis conducted of the effect of the experimental intervention on the belief that AL is effective in curing malaria, considering these four mediators. We find that the odds of believing AL were effective in curing malaria for respondents in the intervention group are 1.17 times as large as the odds for control group [total effect]. Respondents in the control group would also have 1.16 times higher odds of believing AL was effective in curing malaria if they had the same knowledge/behaviuor (mediators) as the respondents in the intervention group [indirect effect]. Finally, respondents in the intervention group would have 1.01 times higher odds of believing AL was effective in curing malaria than the respondents in the control group if the knowledge/behaviour (mediators) would be kept constant at the level of respondents in the intervention group [direct effect]. Taking all the results together, the indirect effect of the intervention on beliefs that works through the mediators is about 96.8% of the total effect.

Table 8 summarizes the size of the indirect effect relative to the total effect for the belief that AL is effective in curing malaria, across waves and by each mediator considered. Estimates show that the experience with the test (columns 1 and 2) and the targeted use of AL (column 3) each explain between 20% and 50% of the indirect effect relative to the total effect, while taking the correct AL dose only explains about 10–12% of the indirect effect. Supplementary Table SA7 extends this analysis to the relative contributions of the other mediator (malaria status) considered in Table 6.

Changes in population beliefs, by type of test

Since the intervention provided RDT through CHW, another important factor we explore is whether the effect of the intervention on population beliefs differs depending on whether individuals decided to go for testing and specifically by the type of test taken. Since in the control group CHWs did not provide any malaria testing, we cannot directly compared treatment and control groups for

Table 8 Relative contributions (%) of the indirect effect to the total effect, for the belief that AL is effective in curing malaria (extended analysis)

% indirect of total effect of mediators:	(1) Ever took test (%)	(2) Ever took RDT (%)	(3) AL targeted use (%)	(4) Correct dose (%)	(5) All mediators (%)
12 months	25.3	53.6	29.6	12.3	110.1
18 months	22.6	18.4	39.3	10.6	75.1
Pooled waves	24.5	27.8	38.9	12.2	96.8

This table presents the results from the mediation analysis of the effect of the intervention on the belief that AL is effective in curing malaria, by wave. The estimates reported are the relative contribution of the indirect effect of the intervention on beliefs that works through the mediators of the total effect, by each mediator and by wave. In cases in which the direct and indirect effects have opposite signs, we run into the so-called case of 'inconsistent mediation'. Inconsistent mediation models are models where at least one mediated effect has a different sign than other mediated or direct effects in a model (Blalock, 1969; Davis, 1985; MacKinnon *et al.*, 2000). In this case, the percentage of the indirect effect (proportion mediated), which explains the total effect can result in a number lower than 0% or bigger than 100%. The estimate in column (5) at 12 months is then not meaningful and should not be interpreted.

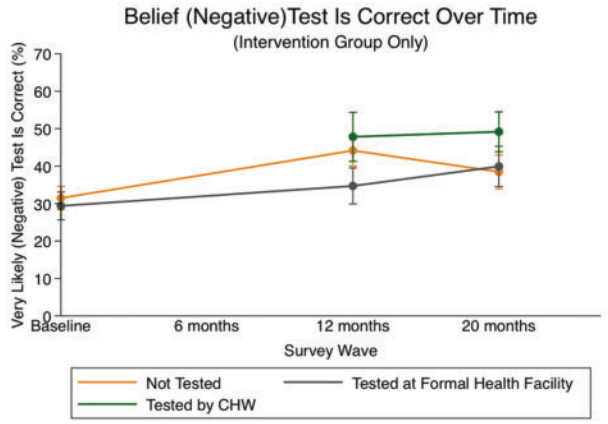

Figure 2 Belief that a negative test result is correct, by wave and type of test (intervention group).

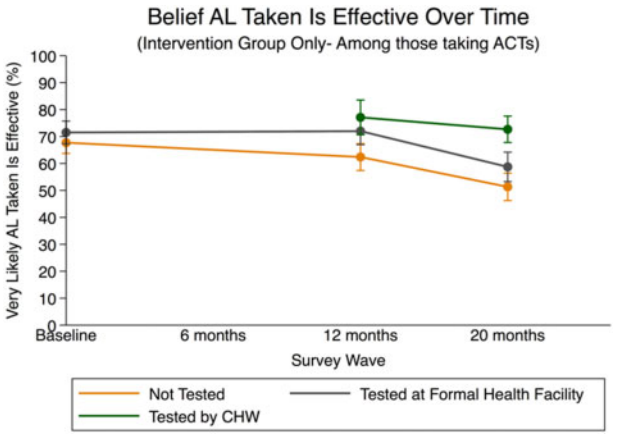

Figure 3 Belief that AL is effective in curing malaria among AL takers, by wave and type of test (intervention group).

malaria testing at the CHW. We, therefore, restrict our comparisons to the treatment group.

Figure 2 shows that the population belief that a negative test result is correct is statistically significantly different between those tested by a CHW and those tested at the health facility, at 12 and 18 months (*P*-values 0.0070 and 0.0437, respectively), confirming that those who had the intervention—and experienced malaria testing with an RDT performed by a CHW—are more likely to believe that a negative test result is correct. Figure 3 shows a similar graph for the belief that AL taken is effective in curing malaria, finding a statistically significant difference at 18 months between those in the intervention group tested at a health facility and those tested by a CHW ($P = 0.0018$). This seems to be in line with the findings in Table 2 that those who were assigned to the experimental intervention—and experienced malaria testing with RDT at CHW—were more likely to believe in AL effectiveness. See Supplementary Appendix B for similar graphs on other beliefs (Supplementary Figure SB1–SB3). To sum up, this graphical evidence suggests that the changes in population beliefs that we observe are due to our experimental intervention, and to a higher proportion of people who experienced malaria testing, specifically with RDTs performed by a CHW.

Discussion

This article takes advantage of an experimental intervention aimed at improving malaria testing and treatment behaviour in rural Western Kenya to study how individual behaviour—in terms of malaria testing and treatment—changes population beliefs. The cluster-randomized intervention, which provided malaria RDT through CHWs for any individual experiencing malaria-like symptoms, and a voucher for a discount on ACTs conditional on a positive test, increased the uptake of malaria testing and improved the appropriate use of ACT at 12 and 18 months (Prudhomme O'Meara *et al.*, 2018).

We find that these changes in behaviour induced by the intervention increased the belief that a negative malaria test is correct as well as the belief that AL is effective in curing malaria (among AL takers). However, we do not find changes in the belief that the febrile illness they had in the previous 48 h was malaria or in the belief that a positive test result was correct. The former may be because the experimental intervention did not change individuals' belief about a specific illness, unless it causes a shift in the distribution of population beliefs for all malaria-like illnesses which is hard to expect. The lack of a change in the belief that a positive test result was correct might be due to the initial high level of trust in a positive test (83%) compared with a negative one (30%), at baseline.

Using mediation analysis, we explore some mechanisms through which these changes in population beliefs happened. We find that 62.4% of the relationship between the intervention and the belief that a negative malaria test is correct is explained by the effect of mediators, such as individual experience with a malaria test or with an RDT, as well as individuals' knowledge and experience with CHWs. Similarly, among AL takers, we find that mediators, such as

the individual experience with a malaria test or with an RDT and, more importantly, the targeted use of AL and taking the correct AL dose, explain 96.8% of the relationship between the intervention and the belief that AL taken is effective in curing malaria. The results on beliefs appear to be driven by individuals' experience with RDTs performed by CHWs, rather than malaria testing at the health facility, confirming the fact that changes in population beliefs at 12 and 18 months are due the behaviour changes caused by the experimental intervention. While we are able to explain almost the entire relationship between the intervention and the belief that AL taken is effective in curing malaria (96.8%) with the mediators included in the analysis, about 40% of the relationship between the intervention and the belief that a negative malaria test is correct is unexplained. Other potential mediators that we lack data on include the individual recovery after a negative test, how many negative tests the respondent had experience with in the past, the experience with RDT of other people in the community, and other actions the individual took to treat their illness in addition to what we observe as researchers.

This study has several limitations. First, because of lack of data on other potential mediators, we are unable to explain the entire relationship between the intervention and the belief that a negative malaria test is correct. Second, we identify which mediators have more explanatory power in the relationship between the intervention and population beliefs, but these estimates are not causal. In addition, the temporal order of the relationship between the mediators and the population beliefs cannot be proved, since data on all these variables are collected contemporaneously. Third, we measure the effects at 12 and 18 months, but we were not able to continue the intervention to measure longer-term effects. These limitations are, however, balanced by the design of the cluster-randomized controlled trial. In fact, the randomized nature of the intervention and the lack of contamination between arms allow us to identify the causal effects of the intervention on beliefs. More importantly, given that the intervention was implemented on a large population, we are able to estimate population-wide impacts of the intervention on beliefs, which enhances the generalizability of our findings.

This study adds on the little quantitative research that investigates the role of beliefs in healthcare choices in the context of malaria burden (Adhvaryu, 2014; Maffioli *et al.*, 2019), and on past research exploring how interventions can change behaviour and beliefs in other health settings (Dupas, 2011). Our results, in the context of malaria testing and treatment, highlight the importance of the malleability of beliefs and how interventions that aim to change behaviours, can also influence population beliefs. In addition, the findings on which mechanisms explain the impacts of the intervention on beliefs speak to which factors (in our case the knowledge and experience with testing and treatment technologies) matter most in changing beliefs, when several things change due to a complex intervention. In our context of malaria burden, it appears that encouraging people to use new technologies—RDT—and guiding appropriate treatment behaviour by subsidizing ACT only for malaria-positive individuals—increases the belief that the technology (RDT) is correct, and that the drug (AL) is effective. Since beliefs have been found to drive individual behaviour in several contexts (see Introduction section for more details), our results might have important implications for long-term changes in behaviour. This is particularly relevant in countries across sub-Saharan Africa where individuals seek care outside the formal sector. Their learning through the technology, sustained by their evolution of beliefs, might guide individuals' future decisions about malaria testing and treatment when they once again develop malaria-like symptoms. Returns to these health technologies would then be amplified. Future research should explore changes in longer-term behaviour for subsequent testing and treatment choices, as a result of changes in population beliefs.

Supplementary data

Supplementary data are available at *Health Policy and Planning* online.

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Conflict of interest statement. None declared.

Ethical approval. The full study protocol has been published (Laktabai *et al.*, 2017). Ethical approval was granted by Moi University Institutional Research and Ethics Committee and Duke University Institutional Review Board. The trial is registered at ClinicalTrials.gov (NCT02461628).

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