Designing Incentive Contracts to Improve the Diagnosis and Treatment of Malaria*

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Abstract

We examine whether a diagnosis contingent incentive contract structure improves the diagnosis and appropriate treatment of malaria, and whether demand or supply incentives for rapid tests (RDTs) and high quality antimalarials (ACTs) only to malaria positive cases better promote socially-optimal antimalarial use. Using a cluster randomized trial design we randomize patient subsidies and pharmacist performance incentives. We find that both patient subsidies and provider incentives increase RDT testing uptake by 25 percentage points, on average, and lead to significant improvements in appropriate antimalarial use, largely due to malaria negative patients opting out of taking unnecessary malaria medication. The increase in ACT purchase appears to be concentrated among those that find out that they are malaria positive. However, the reduction in ACT purchase is concentrated in the group that finds out that they were malaria negative and in the incentivized treatment groups. This suggests that the reduction in ACT purchase is driven by a combination of patient specific diagnosis information and incentives. We find evidence that patient subsidies and provider incentives operate through different channels: patient subsidies result in significantly lower RDT prices paid by patients, while provider incentives induce pharmacists to provide more comprehensive counseling. Finally, we find that all three incentive interventions are cost-effective approaches to improve appropriate antimalarial use in pharmacies. Taken together, these results suggest that appropriately calibrated and targeted financial incentives are promising for changing patient and provider behavior, with implications for quality of care.

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1 Introduction

A key feature of healthcare markets is the role of information Arrow 1963. The process of caring for a patient includes both a diagnostic (information) phase to assess disease and a treatment decision. Existing models of physician treatment decisions and empirical implementations do not distinguish between these phases. Most focus on the ultimate treatment which is a result of both components.

Existing models of a (relatively) informed provider responding to incentives (see McGuire 2000 for a review) and influencing both patient demand and selling treatments generates . Less attention has been paid to the distinction in treatment between correct diagnosis (information) and treatment decisions. When there is a role for matching patients to care, acquiring information through diagnostic testing has critical implications for efficiency.

In this paper we explore the interaction of diagnostic decisions, patient beliefs and treatment decisions in the context of diagnosis and treatment for malaria.

Both over- and under-treatment of medical conditions are ubiquitous worldwide and can have serious negative consequences for patient outcomes (Das and Hammer 2014; Whitehead, Dahlgren, and Evans 2001). For example, studies in both the US and China have found high levels of unnecessary antibiotic prescriptions (Currie, Lin, and Meng 2014; Fleming-Dutra et al. 2016), which may affect patient outcomes and contribute to growing rates of drug resistance. Similarly, studies across sub-Saharan Africa have found that large shares of malaria-positive patients go untreated while large shares of malaria-negative patients receive antimalarials Ansah et al. 2010; J. Cohen, Pascaline Dupas, and Schaner 2015; J. L. Cohen et al. 2013; O'Meara, Mohanan, et al. 2016). However,

We investigate the extent to which financial incentives can be used to cost-effectively improve the allocation of anti-malarial drugs by increasing the treatment of malaria positive patients and reducing the unnecessary treatment of malaria negative patients. Specifically, we use a diagnosis-contingent contract structure that provides incentives to increase the use rapid diagnostic tests (RDTs) to determine if a patient is malaria positive with additional

incentives to treat using front-line anti-malaria drugs (Artemisinin Combination Therapies – ACTs) only if malaria positive. The contract encourages appropriate treatment both through generating information about illness status (i.e. malaria positive or negative) from the RDT and through the diagnosis contingent financial incentives for ACT use. This way the incentive contract encourages appropriate treatment and discourages unnecessary treatment.

This contract represents an innovation in the structure of payment incentive contracts studied. Most consumer subsidies for health products and health care as well as performance pay schemes pay a flat fee for all covered services, where fees are not differentiated based on diagnostic information. In contrast, our incentive contract only pays for treatment contingent on a positive diagnosis for a treatable medical condition. The contract strengthens medical decision making by providing incentives to improve both diagnosis and treatment.

Using a cluster randomized field experiment in malaria-prone counties in Kenya, we evaluate the effect of the diagnosis contingent financial incentives on malaria testing and treatment decisions. We further investigate whether financial incentives are more effective when they are given to patients through subsidies (demand-side) versus to providers through performance incentives (supply-side), or a combination. We also examine the mechanisms by which the incentives work. Demand- and supply-side incentives of the same magnitude should result in the same impact on consumer demand if the supply-side subsidies are simply fully passed through to consumers in terms of reduced prices. The impact may differ, however, if some of the incentives are captured by the provider and not passed through to patients, or if providers encourage increased demand through non-price mechanisms such as improved counseling. We also investigate the extent to which the effect of the incentives contract on treatment (ACT use) is driven by information (i.e. malaria status) versus financial incentives.

Malaria is an important disease to study clinical decision-making because it is a well-understood illness, it has a high disease burden, and nearly all deaths and serious illness are preventable through effective and inexpensive medication (WHO 2021). RDTs are widely available across high-burden areas in sub-Saharan Africa and are highly accurate in con-

firming the presence or absence of malaria parasites in a symptomatic patient. In practice, however, few malaria patients are diagnosed prior to getting treated. Low diagnostic testing contributes to a gap between treatment and need; missed diagnoses result in more severe avoidable illness and over-prescription of anti-malaria drugs to malaria-negative patients can lead to heightened drug resistance in the population.

The literature identifies several potential reasons as to why diagnostic testing is low. Patients may not demand tests because of (i) strong prior beliefs about their malaria status – i.e., a low perceived value of information from testing (Maffioli et al. 2019), (ii) the cost of the test is prohibitive (J. Cohen, Pascaline Dupas, and Schaner 2015; O'Meara, Menya, et al. 2018), and (iii) they do not want to wait for the diagnostic test result – i.e., impatience. Moreover, providers may not prescribe a test prior to treatment because (i) they have established practices of symptom-based diagnosis – i.e., established norms and habits (Mbonye et al. 2013), (ii) they are optimizing perceived patient preferences (Lopez, Sautmann, and Schaner 2020), and (iii) they have profit motives (Currie, Lin, and Meng 2014).

We explore these issues in the context of an RCT with pharmacies in high malaria prevalence counties in Kenya, where over 3.5 million people fall ill with malaria annually. The study population lives near Lake Victoria and on the coast, areas that are most vulnerable to infection (Disease Control and Prevention 2018; Initiative 2021). Over half of malaria patients access treatment via pharmacies, often the preferred access point for primary care given pharmacies' convenience and reliable presence even in areas that are under-served by public health care clinics and hospitals (Burton et al. 2011; Musuva et al. 2017). Given that pharmacies play a crucial role in providing access to malaria case management in Kenya, it is essential that they provide appropriate diagnostic testing and low-cost, effective and appropriate medicines for treatment.

We sequentially randomized 140 pharmacies into either a status quo control group or one of three treatment groups, each with a two-part incentive: (1) patient subsidies for RDT tests and for the anti-malarial drugs (Artemisinin Combination Therapies – ACTs) conditional on

a positive test; (2) pharmacy incentives for RDT tests, and for prescribing ACTs conditional on a positive test; and (3) combined incentives (patient subsidies and pharmacy incentives) for RDT and ACTs for confirmed malaria-positive cases. The total value of the subsidies was held constant across the three intervention arms. This design allowed us to evaluate the impact of a two-part incentive structure where payouts depend on the full continuum of care (and diagnostic information) as well as to examine the causal effect of targeting that incentive to the patient versus the provider.[1]

We find that both patient subsidies and provider incentives are effective at increasing RDT uptake and at improving targeting treatment to malaria-positive patients. Patient subsidies increase the likelihood that a symptomatic patient takes a rapid test by 27 percentage points over a control group rate of 8 percent.[2] Pharmacy incentives increase the likelihood of rapid test uptake by 20 percentage points, which is statistically indistinguishable from the demand-side approach.

Absent any interventions, 87% of suspected malaria patients purchase ACTs, of which as many as 66% are doing so unnecessarily because they do not have malaria. This represents a high baseline level of medication waste, and means that a large share of patients may experience delays in getting appropriate care. We find that the incentives lead to an overall decline in ACT usage of 14 percentage points, which can be explained by the increase in testing. On the one hand, we find that both demand and supply incentives increase the likelihood that a patient purchases ACTs combined with a diagnostic test by 7 percentage points. On the other hand, we see large declines (16-22 percentage points in demand- and supply-side arms) in the likelihood that patients purchase malaria treatment without a diagnostic test. We find that these offsetting effects are due to improvements in treatment targeting, and in particular, malaria-negative patients listening to that test result and electing to forego un-

[1]Prior literature has studied the impact of demand-side subsidies, but not provider incentives, on malaria care, finding them to be effective at improving testing but not at improving test result adherence (J. Cohen, Pascaline Dupas, and Schaner 2015; O'Meara, Menya, et al. 2018; O'Meara, Mohanan, et al. 2016).

[2]This result is consistent with what has been found in prior literature on consumer subsidies for for RDTs and other health goods.(J. Cohen, Pascaline Dupas, and Schaner 2015; Pascaline Dupas 2014)

necessary antimalarial purchases. The increase in ACT purchase appears to be concentrated among those that find out that they are malaria positive. However, the reduction in ACT purchase is concentrated in the group that finds out that they were malaria negative and in the incentivized treatment groups. This suggests that the reduction in ACT purchase is driven by a combination of patient specific diagnosis information and incentives.

We also find that while the patient subsidies for RDTs resulted in significantly lower prices being paid by patients, none of the provider incentives were passed through to lower prices. Patient subsidies lower prices paid by about 43% (yielding a price elasticity of demand of 7.86). We do, however, find that the pharmacist provided more explanation of diagnosis and counseling of treatment based on the test result – i.e., patient specific information. Thus, the financial incentives seemed to work through an information pathway. The demand subsidies induced more patients to purchase RDTs that provided accurate illness status information leading to more appropriate use of RDTs. The provider subsidies lead pharmacists to promote the value of RDTs leading to similar results.

We also conduct a cost-effectiveness analysis, which provides a more complete picture of how to efficiently allocate resources. The improvements in cost-effectiveness as compared to the status quo that we find are largely due to the fact that as a result of these interventions, we find significant reductions in malaria-negative patients taking unnecessary antimalarials. The outcome of interest for our cost-effectiveness measures is the incremental cost per additional patient appropriately treated with ACTs (thus, is malaria positive). We include direct costs of over-treating malaria negative patients and the time costs for patient seeking care. We find that the patient subsidy and the provider performance incentive interventions are significantly cost-saving, relative to the control group. The hybrid approach costs $36 for each additional patient that purchases an ACT and is malaria positive, compared to the status quo control group. This suggests that all interventions are relatively low cost when compared to the status quo, and that patient subsidies and pharmacy incentives may be cost-saving depending on the perspective taken.

This paper makes five contributions. First, it adds to our understanding of how incentives targeted at the demand-side or the supply-side can affect decision-making. Within general economics, we build on papers like Busse, Silva-Russo and Zettelmeyer that look at how incentives targeted to either consumers or sellers affect consumer prices and demand (Busse, Silva-Risso, and Zettelmeyer 2006). We also contribute to this conversation in the health economics literature. Financial incentives are well-established tools used around the world to promote a wide range of health behaviors. Typically, demand and supply side incentives are studied independently, in this paper we compare them directly and put the two literatures in conversation with each other. Demand-side incentives all operate based on the assumption that either price itself is a barrier to adopting a health behavior, or an incentive can nudge people to overcome other non-pecuniary barriers. Price experiments for health treatments have shown that people do not respond uniformly to prices, and instead the nature of the health decision and timing of the benefits affect demand elasticity (J. Cohen, Pascaline Dupas, and Schaner 2015; Dow, White, and Bertozzi 2016; P. Dupas and Miguel 2017; Pascaline Dupas 2014; O'Meara, Mohanan, et al. 2016).

On the supply side, providers influence patient health decisions using their expertise, preferences, and sometimes biases which can have significant effects on quality of care. They can act as gatekeepers to reduce unnecessary medical treatments, or promote overuse (Currie, Lin, and Meng 2014; Lopez, Sautmann, and Schaner 2020). Performance-based financing mechanisms in low- and middle-income countries reward providers for both quantity and quality of health services delivered by paying for key outputs (Ahmed et al. 2023; Basinga et al. 2011; Gertler, Giovagnoli, and Martinez 2014; Miller and Babiarz 2013; Peabody et al. 2014; Witter et al. 2012; Yip et al. 2014). These studies suggest that properly incentivizing providers can lead to improvements in health care utilization and key health outcomes, but the evidence has been limited to a relatively narrow set of indicators and outcomes. Additionally, the literature on performance incentives focuses on the price effects, but ignores mechanisms through which incentives operate. Our study provides evidence on behavioral

channels through which provider performance incentives may impact quality.

Second, we contribute to these two strands of literature by innovating in how health financing contracts are structured. Conditional cash transfers for preventive health visits, for example, incentivize health care utilization by lowering the cost of care to patients. In the US, insurance products that have modest copays or deductibles operate in the same way - by lowering the price patients pay. These examples, as well as other demand-side incentives for healthcare, highlight how these financing models typically operate - they reimburse a flat rate for services used through lower prices/copays (Arrow 1978; Cutler and Zeckhauser 2000; McGuire 2000; Pauly 1980). Performance pay models that reward providers either directly through bonuses tied to services provided (see (Ahmed et al. 2023; Basinga et al. 2011; Gertler, Giovagnoli, and Martinez 2014; Miller and Babiarz 2013; Peabody et al. 2014; Witter et al. 2012; Yip et al. 2014) for examples) or indirectly through capitation have a similar structure. Payments are typically made based on services provided, and do not explicitly take into account diagnostic information when setting copays for various services.[3] We propose a different type of contract: one that explicitly pays (charges) differentially for services based on diagnostic information. In our setting, patients and providers are incentivized to test for suspected malaria - this step mirrors standard fee for service models. Next, they are further incentivized to get treated only if patients receive a positive diagnosis. This fits in with other literatures on performance pay based on outcomes, including applications for medical doctors and teachers (Campbell et al. 2009; Podgursky and Springer 2007; Prendergast 1999).

Third, it adds to the literature on how personalized health information and financial incentives can be combined to change health behavior. Information combined with financial incentives has shown more promise in encouraging health behavior adoption (Pascaline Dupas 2011; Ma et al. 2014; Meredith et al. 2013). But, the quality of the information matters: general health information tends to be less effective in changing individual behaviors than individually tailored messages targeted at the key decision-makers (Gong 2015). Studies that

[3]Though, of course, we acknowledge that patients with different medical needs will pay different amounts for their care because services needed will be diagnosis-dependent.

have examined whether information provided by a malaria diagnostic test changes treatment-seeking behavior have found mixed results – information is effective in steering some patients towards appropriate treatment options, especially when coupled with an incentive, but many elect to ignore test results when making treatment decisions (J. Cohen, Pascaline Dupas, and Schaner 2015; O'Meara, Menya, et al. 2018). This study leverages the two steps of the testing and treatment decision by providing a financial incentive for treatment conditional on the personalized health information provided by the test. We test the extent to which appropriate malaria treatment use is a result of information (RDT result) or an added financial incentive (for ACT), contributing to the long literature on the role of information and information asymmetries in health decision-making (Arrow 1978).

Fourth, this paper contributes to our understanding of how pharmacists make decisions. Pharmacists are important care providers in many low- and middle-income country contexts and are under-studied in the literature on provider motivation. Prior studies of financial incentives for malaria care in Kenya have used vouchers that patients could redeem at pharmacies but have not studied the pharmacist's role in malaria case management directly.[4]

Finally, we develop a cost-effectiveness framework to quantify the societal costs of over-treatment with antimalarials and benefits of appropriate malaria treatment targeting from an implementer and societal perspective. The framework that we develop for assessing cost-effectiveness can be extended to other settings that are characterized by diagnostic testing availability and over-treatment that can have negative social consequences.

The remainder of this paper is organized as follows: Section 2 discusses the conceptual framework and hypotheses for the main research questions and outcomes. Section **??** describes the experimental design, data and methods. Section 3 presents experimental results on the main outcomes and effects, mechanisms, and cost-effectiveness. Section 4 concludes.

[4]However, there is at least one other ongoing study which tests pharmacy incentives for malaria testing and treatment (Woolsey et al. 2021).

2 Conceptual framework

The primary goal of clinical decision-making is to ensure that patients who seek care are given the diagnosis and treatment recommendations that are best suited to their needs. For many common illnesses, providers can rely on clinical guidelines that provide a set of decision rules to aid in interpreting noisy and incomplete symptom signals to diagnose and treat. For malaria, clinical guidelines are clear: confirm the malaria diagnosis with either a rapid diagnostic test or microscopy prior to administering antimalarials. Rapid tests for malaria are widely available, affordable, and can be administered by a wide range of health professionals. Despite this, most malaria cases are treated without any formal diagnosis.

Two types of errors can occur when antimalarials are administered without a diagnostic test: overtreatment of malaria-negative individuals with antimalarials, and undertreatment of malaria-positive individuals with ACTs (Figure 1). Overtreatment occurs when malaria negative patients still get prescribed antimalarials, and can lead to delays in correct care for individual patients,[5] and to increases in drug-resistant strains of malaria.[6] Undertreatment occurs when malaria-positive patients do not get prescribed ACTs, which can lead to delays in appropriate care and increased complications due to illness.

Below is a conceptual framework that illustrates patient and pharmacist decision-making[7] Then, we aggregate the individual testing and treatment decisions to the population level and discuss how these parameters are measured in the experimental design.

[5]In practice, there are different possible diagnoses given a set of observable symptoms for a malaria-negative patient, including harmless viral infections, and more serious problems that require different treatments to cure.

[6]This is a well-founded public health concern. Chloroquine-resistant P. falciparum has spread to nearly all areas of the world where falciparum malaria is transmitted, making this drug ineffective (World Health Organization 2018).

[7]This conceptual framework builds from models developed in Lopez et al 2020 Lopez, Sautmann, and Schaner 2020 and Cohen, Dupas and Schaner (J. Cohen, Pascaline Dupas, and Schaner 2015).

2.1 Patient and pharmacist decisions

Patients and pharmacists make a series of coordinated decisions, which can be influenced by a variety of factors, to appropriately manage a suspected malaria case. We illustrate this sequence for patients in Figure 2. The starting point for this framework is that the patient is symptomatic and has decided to seek care at a pharmacy.[8] The first decision that the patient makes is whether or not to take a diagnostic test (Step 1 in the figure). The decision to test depends on factors like availability, the pharmacist's recommendation, cost, and the patient's own beliefs about her illness status. If the diagnostic test is expensive, especially relative to the treatment, the patient may avoid purchase due to low willingness or inability to pay.

If the patient does not get diagnosed, she does not gain any additional information about her illness status, and she must decide whether to purchase ACTs or not. If the patient does get diagnosed, she learns her malaria status with a high degree of certainty (Step 2 in the figure). At this point, the treatment choices are the same as if she did not get diagnosed, but the clinically appropriate course of action is clear (Step 3 in the figure). From a public health perspective, the optimal end states are illustrated in the green boxes in the figure: malaria positive patients obtaining ACTs and malaria negative patients not obtaining ACTs or other antimalarials.

The interventions tested in this study aim to align patient and pharmacist objective functions by using financial incentives that incentivize testing and only treating malaria-positive cases. For patients, this reduces the cost barrier to testing and incentivizes use of ACTs if appropriate. The fact that malaria-negative patients receive no discount for medications (so, would be responsible for paying full price) further disincentivizes patients from purchasing antimalarials unnecessarily. By incentivizing pharmacists to diagnose, they

[8] Because this study's target population is febrile patients who seek care at pharmacies, the conceptual framework restricts the scope of the decision to after a patient has already made the decision to seek care in the private sector as opposed to either (a) not seeking care at all, or (b) seeking care at a public clinic. This is important, as a different starting point may yield different types of decisions with associated implications for program design and patient outcomes.

may encourage patients to get tested (supplier-induced demand). Additionally, incentivizing patients to make treatment recommendations that are linked to the diagnostic test outcome may also encourage patients to choose treatment options that are based on clinical need, rather than perceived illness status. Supplier-induced demand in this setting can actually encourage use of high value care, and move patients more towards optimal outcomes. For pharmacists, these incentives make diagnostic testing more attractive from the perspective of firm profitability by compensating for any lost medication sales that would come from malaria-negative patients choosing to not purchase antimalarials.

2.2 Experimental treatments

The treatment arms incentivized patients, pharmacists, or both to use malaria rapid tests and to use ACTs when patient tests positive. The magnitude of the incentive was held fixed at 200 Kes (~$2 USD) across all three treatment arms.[9] This amount was either given entirely to the patient in the form of a subsidy, entirely to the pharmacy in the form of an incentive divided between the pharmacy owner and attendant, or split between the patient and the pharmacy in the combined arm. The four intervention arms are as follows (also in Appendix Table C1):

1. Control group (C): pharmacy is an active user of the basic sales and inventory management digital platform, and pharmacy manages their own stock of malaria diagnostic tests and treatments. Patients purchase diagnostic tests and treatment at market prices, and pharmacies stock and price these products according to their business practices.

2. Patient subsidy group (T1): In addition to the features present at control pharmacies, clients who seek care for suspected malaria cases are eligible for a subsidized rapid test

[9]The incentive amount is consistent with prior literature, was determined after a pilot phase, and was calibrated to ensure pharmacy profitability would not be adversely affected, compared to the status quo.

(90% subsidy, a 10 Kes copay) and a subsidized ACT (80% subsidy, a 30 Kes copay) conditional on a confirmed positive malaria diagnosis.

3. Pharmacy incentive group (T2): In addition to the features present at control pharmacies, the pharmacy owners receive an incentive to sell the rapid test (90 Kes), and an additional incentive to prescribe ACTs to malaria-positive patients (80 Kes). Pharmacy attendants receive a 30 Kes incentive for recording transaction information in the malaria case management platform and completing the sale of incentivized products.

4. Combined group (T3): In addition to the features present at control pharmacies, the clients are eligible for discounted rapid tests (60% subsidy, a 40 Kes copay) and discounted ACTs conditional on a positive test result (60% subsidy, a 60 Kes copay). Pharmacy owners receive an incentive to sell rapid tests (15 Kes), and an additional incentive to prescribe ACTs to malaria-positive patients (15 Kes). Pharmacy attendants receive a 30 Kes incentive for recording transaction information in the malaria case management platform and completing the sale of incentivized products.

The interventions were operationalized by Maisha Meds, a Kisumu-based healthcare social enterprise that provides sales and inventory management support to small pharmacies and clinics throughout Kenya. All pharmacies in the sample were existing users of the Maisha Meds sales management platform, which records all pharmacy transactions and product stock. [10] Pharmacy staff received training on the importance of diagnostic testing (all arms), the malaria case management tool and proper rapid test administration (intervention arms), and rapid tests and ACTs were provided on consignment through the program (intervention arms).

[10] The incentive interventions were integrated into this digital platform and managed centrally by the Maisha Meds team. Subsidy and incentive amounts were automatically calculated based on the products that are being bought/sold and verified by implementation staff independent of the pharmacies prior to disbursement to ensure implementation fidelity.

2.3 Sample selection and pharmacy randomization

Within study counties, all pharmacies that were part of the Maisha Meds network were mapped and screened for eligibility. To ensure adequate regulatory oversight and homogeneity among study sites, only licensed pharmacies that were registered businesses with Kenya's Pharmacy and Poisons Board at the time of onboarding were eligible to participate in the study. Additionally, they needed to be active users of the Maisha Meds digital sales and inventory management tool, be at least 0.5 km away from other study sites,[11] and be willing to be randomized to one of the study arms.

In total, 140 pharmacies across thirteen counties in the malaria endemic and epidemic areas of Kenya's western regions were selected to be part of the study. Pharmacies that met these criteria were sequentially randomly assigned to one of the four arms in waves, stratified on average monthly malaria product sales volumes (above/below median), urban/rural, location of pharmacy in lake endemic county, and participation in earlier pilot study phase.[12] Figure 5 shows the geographic span of the experiment across the target regions in Kenya and the final selection of pharmacies. Because interventions were randomized at the pharmacy level, every person seeking care for suspected malaria was eligible for the same intervention.

2.4 Experiment timeline and data collection

See Table 1 for study timeline and a description of the primary sources of data.[13]

We use the following data sources for analysis:

[11] The average distance between study sites is 6.24 km (range of 0.5 km to 46.2 km).

[12] Randomization was done in Stata 16 by the lead investigator.

[13] The study was initially planned to begin in June 2020, but was delayed due to COVID-19. The research and implementation teams followed Kenyan and UC Berkeley CPHS guidelines for conducting research while keeping study staff, implementation staff, and study subjects safe from COVID-19. All personnel and pharmacy staff were required to wear masks, maintain 1 meter distance from each other, and sanitize hands frequently. The research and implementation teams provided adequate PPE and hand sanitizer for all study and implementation personnel. Pharmacies were required by the Kenyan government to have all staff wearing masks, and have hand washing stations for staff and pharmacy clients, and pharmacies in our sample were compliant with these requirements during the study period. The pharmacy onboarding, patient exit survey, standardized patient visits, and control group testing activities were all done in person following appropriate COVID-19 precautions. The pharmacy baseline surveys were conducted over the phone.

1. *Baseline data:*

   (a) Pharmacy owner survey: survey about number of staff, pharmacy business operations, patient volumes, pharmacy characteristics, costs and revenues, and knowledge of malaria case management.

   (b) Pharmacy staff survey: survey about malaria case management knowledge, worker motivation, and use of the digital platform used to manage sales and inventory.

2. *Administrative data:*

   (a) Sales data: continuously collected transaction data including prices and quantities of products purchased, location, date, and time of sale, and pharmacy staff who made the sale for over 50,000 malaria-related patient encounters between June 2021 - February 2022.[14]

   (b) Malaria case management data: continuously collected transaction data on all rapid test and treatment purchases made through incentive program, including information on age/gender of patient, rapid test result, prices and quantities of medications purchased, location, date, and time of sale. Over 8,000 malaria transactions logged between June 2021 - February 2022.

3. *Patient exit survey data:* survey with a random sample of 1654 eligible adult pharmacy clients across all study sites (12.6 clients/site).[15] This survey includes information on quality of care, symptoms, prices and quantities of medications and diagnostic tests purchased, beliefs about their illness status, malaria test result if applicable, and basic demographics.

[14] Prices observed in the data are retail prices set by pharmacists in the digital tool.

[15] In order to be eligible, clients must have sought care for malaria symptoms for themselves or a family member present at the pharmacy with them. Trained research staff visited each study pharmacy during an unannounced 5 day period, and screened all patients who exhibited malaria-related symptoms or purchased malaria products for eligibility. There were 1674 possible respondents screened, and 1654 respondents who completed the survey.

4. *Testing subsample data:* data on test positivity from testing of random subset of 230 pharmacy clients at control group sites to obtain test positivity rate in a sample unaffected by the interventions (8.5 clients tested/site, 28 sites participated). Additional test positivity data from administrative records from 10 control group pharmacies that kept records of tests conducted (N=2547) on-site between January-February 2022.

5. *Endline data:*

   (a) Pharmacy owner survey: survey about number of staff, pharmacy business operations, patient volumes, pharmacy characteristics, costs and revenues, and altruistic tendencies.

   (b) Pharmacy staff survey: survey on malaria case management knowledge, worker motivation, use/familiarity with the digital platform used to manage sales and inventory and manage malaria cases, and altruistic tendencies.

2.5 Empirical strategy

2.5.1 Take-up of the intervention

We measure trial take-up as the subset of eligible pharmacies in the study area that consented to participate in the trial. The total number of eligible pharmacies in the study catchment area was obtained from the administrative records of the implementing partner. Each consenting pharmacy agreed to manage their sales through the digital tool, and to offer incentives (either supply- or demand-side) for malaria testing and treatment if assigned to one of the intervention arms.

We then determine the relationship between trial take-up and eight pharmacy-level characteristics: number of months active on digital sales management tool; baseline (2019-2020) average monthly malaria product sales, high quality malaria treatment (ACT) sales, and rapid diagnostic test sales; participation in earlier study phase,[16] urbanicity, location in a

[16] 60 pharmacies participated in a Phase 1 of the study between November 2020-February 2021, where

lake endemic county, and pharmacy type. In order to determine whether trial take-up is related to any of these covariates, we conduct pair-wise t-tests comparing these characteristics across pharmacies that declined to participate and those that elected to participate.

2.5.2 Treatment effects on testing and treatment targeting

We present all results of the program impact on testing and treatment targeting in terms of comparisons between each intervention arm and the control group (status quo pharmacy care experience). Additionally, we discuss any significant differences between demand-side incentives and supply-side incentives, and across all three intervention arms and compare to the minimum detectable effects that the study was powered to detect. All analyses are conducted at the patient level[17], and an intention-to-treat (ITT) framework is used. Some clients at intervention pharmacies refuse to purchase rapid tests and treatments through the intervention platform (at a fixed reduced price, in T1 and T3) and will elect to make other purchases or none. By including all eligible malaria patients in an ITT analysis, rather than only patients who elect to take up the intervention assigned to the pharmacy, we preserve the unbiasedness benefits of randomization. The analyses specified in this section were pre-registered in a pre-analysis plan (AEARCTR-0004705). We discuss any deviations from the pre-analysis plan where relevant.

For all binary outcomes, we report effects from adjusted logistic regression models using the following regression framework.

$$Pr(Y_{ip}) = expit(\beta_0 + \beta_1 T_{1ip} + \beta_2 T_{2ip} + \beta_3 T_{3ip} + \lambda_s + \boldsymbol{X}_p + \epsilon_{ip}) \tag{1}$$

where Y_{ip} is a malaria testing or treatment outcome, T_{jip} are treatment assignment indicators for each intervention j for individual i seeking care at pharmacy p, with the control

different levels of patient subsidies for malaria testing and treatment were randomized to patients. This study phase was stopped because of insufficient take-up and operational complexity, and these sites were balanced across treatment arms in the full study sample.

[17]This is equivalent to febrile illness episode level since most patients in our sample only have had one symptomatic pharmacy visit during the study period.

group as the reference category, λ_s are strata fixed effects, and ϵ_{ip} is the error term. We include variables that had significant imbalance with the control group at the 10% level or below at baseline (Tables 2 and 3)) as covariates in this adjusted model ($\boldsymbol{X_p}$), as specified in the pre-analysis plan. The β terms represent the log-odds of the treatment effect of each intervention relative to the control group, as percentage point changes. We report all results in terms of marginal effects in relation to the control group mean. We also report p-values from Wald tests comparing the marginal effect coefficients of the interventions to each other. Results of unadjusted models (excluding $\boldsymbol{X_p}$) are consistent with findings from the adjusted models, and can be made available upon request.

In addition to looking at each intervention separately, we report results from pooling the interventions, to measure overall impact of any incentive program on outcomes of interest. This pooled regression specification was not pre-specified in the analysis plan, and is below:

$$Pr(Y_{ip}) = expit(\beta_0 + \beta_{pooled}\boldsymbol{T}_{ip} + \lambda_s + \boldsymbol{X}_p + \epsilon_{ip}) \tag{2}$$

All results are from administrative transaction data from the full sample of patients who sought malaria care in study pharmacies, unless otherwise specified. For results that look at treatment purchases conditional on malaria status, we conduct the analysis at the pharmacy level because we have site-level test positivity and negativity rates for all groups. To calculate test positivity and negativity rates, restrict the intervention-group sample to patients whose malaria diagnosis is known because they were diagnosed through the incentives intervention. We construct a comparison group from control group sites for this subset of patients using test positivity data collected as part of the study by independent enumerators and pharmacy-reported test results and imputing the share of patients who purchased ACTs at control sites that were malaria-positive or not. More details on this imputed control group can be found in Appendix 4.3.

The mechanisms analysis uses survey data collected from Standardized Patient visits. We conduct analysis at the site-level for the incentive pass-through analysis because there is

very little within-site price variation for malaria tests and treatments during the period of time when SPs conducted their visit. We conduct SP visit-level analysis for the information channel, as there is sufficient variation in the SP visit experiences within pharmacies to justify this choice.

2.5.3 Cost-effectiveness analysis

In order to analyze the efficiency of each intervention, we conduct a cost-effectiveness analysis where the measure of interest is the incremental cost per additional patient who is appropriately treated with ACTs (so, is malaria positive). We use standard formulas to calculate the ratio of the change in benefits to the change in costs across each intervention arm compared to the status quo. Benefits are defined as the change in patients taking ACTs appropriately (patients must be malaria positive), and costs are defined as the sum of the incentive costs, out of pocket costs for tests and treatment, and the direct costs of over-treating malaria negative patients.

The final cost-benefit ratio formula used is below:

$$\frac{Beneficiaries_t - Beneficiaries_c}{TotalCost_t - TotalCost_c}$$

where $t \in (1, 2, 3)$ denotes each treatment arm and c denotes the control group (status quo). The term *Beneficiaries* represents the total number of patients who take ACTs appropriately, and the term *Total Cost* represents the intervention costs, out of pocket costs for tests and treatment, and the direct costs of over-treating malaria negative patients. We estimate incremental cost-effectiveness ratios (ICERs) from the perspective of the program implementer (including only program costs) and from a societal perspective (including program costs, costs incurred by patients for tests and treatments, and direct costs of over-treating malaria negative individuals). Full details on the cost-effectiveness analysis, including all formulas, assumptions, and data sources for each parameter, can be found in Appendix 4.

2.6 Trial take-up and sample characteristics

Incentives for rapid diagnostic tests and ACTs were randomized across 140 pharmacies at baseline, with 35 assigned to the control group (25%), 35 assigned to the patient subsidies group (25%), 35 assigned to the pharmacy incentives group (25%), and 35 assigned to the combined group that received both patient subsidies and pharmacy incentives (25%). Tables 2 and 3 report the experimental balance checks at baseline (for pharmacy-level variables from the administrative data and survey data, respectively), and shows that randomization was fairly balanced across a large set of pre-specified covariates. Out of 84 tests conducted, 8 are significant at the 10 percent level or more. When we conduct a joint test for orthogonality using a multinomial logit model with treatment assignment as the categorical outcome, We find that the χ^2-test produces a p-value of 0.46. This suggests that these covariates are not jointly predictive of group assignment. In the adjusted models, we control for covariates that were unbalanced at baseline from comparisons with the control group, consistent with the pre-analysis plan.

We measure fidelity to implementation as whether there were any malaria transactions logged in the digital sales tracking platform for a study pharmacy during the study period (June 2021-February 2022). By this metric, 8 facilities out of 140 were inactive during the study period (1 in the patient subsidy arm, 2 in the pharmacy incentive arm, 2 in the combined arm, and 3 in the control group). For the remaining facilities, the number of active facilities by month can be found in Figure 6, and the number of facilities actively selling incentivized malaria tests and treatments can be found in Figure 7. The pharmacy onboarding occurred between June-December 2021, so the increase in the number of active facilities over this time period is due to pharmacies being onboarded to the study in a staggered way.

Randomization was done prior to enrolling facilities in the study for sites that met all eligibility criteria, due to operational necessity of conducting in person site visits to introduce the program and the study at the same time. Appendix Table C2 reports balance

on baseline variables obtained from the administrative data between facilities that, when offered participation in the program and study, accepted (in sample) and those that declined (refusals). Column 3 reports the differences between the two group means and the significance stars from a t-test comparing the difference in group means. Facilities that declined to participate had been using the digital sales platform for longer than facilities in the sample frame. No other meaningful imbalances were found. Appendix Tables C3 and C4 report descriptive results from regressing the primary and secondary outcomes on the sample baseline characteristics.

3 Results

3.1 Impact on diagnosis and treatment of malaria

The intervention's primary objective was to increase diagnostic testing uptake and improve malaria treatment targeting among pharmacy clients with suspected malaria. So, we present findings on these two dimensions of appropriate malaria case management in turn and explore mechanisms.

Mean levels of rapid diagnostic test uptake in control group pharmacies are low, which is consistent with trends found across the full pharmacy sample prior to the start of the experiment (Appendix Figure C1) as well as with existing research on rapid diagnostic test use in pharmacy settings across East Africa. Only 8% of patients who sought care for malaria-related symptoms in control group pharmacies purchased a rapid diagnostic test prior to obtaining treatment (Table 4). Overall, the incentives interventions increased rapid diagnostic test use substantially. Patients who sought care in treatment pharmacies were 25 percentage points more likely to purchase a diagnostic test before getting treated with antimalarials (column 1, Table 4). Looking at each incentive arm separately, as we do in column 2, we find comparable effects across all three arms. Patient discounts alone resulted in a 27 percentage point increase in rapid test uptake, and both pharmacy incentives and the

combination of patient discounts and pharmacy incentives resulted in a 20 percentage point increase, with no statistically significant difference across the three arms. So, on average we find a more than 300% increase in the use of rapid diagnostic testing as a result of the intervention.

Both demand- and supply-side incentives improved rapid diagnostic testing uptake, but did they have any impact on appropriate use of antimalarials? We discuss results on treatment targeting from Table 5, again looking at the pooled treatment effect and each of the three interventions arms separately. The vast majority of control group patients who sought care for suspected malaria purchase ACTs (87%).[18] We find a significant decrease in ACT uptake overall, of 14 percentage points on average, and between 9-15 percentage points when looking at each incentive intervention separately (but again, the three arms are statistically indistinguishable from each other).

When we separate this aggregate measure into its two components: ACT uptake with an accompanying diagnostic test, and ACT uptake without an accompanying diagnostic test, we can better understand this decline. Of the control group patients who purchased ACTs (87%), only 6% of them did so with an accompanying diagnostic test. Across the three intervention arms, we find a 7 percentage point increase in the share of patients who purchased ACTs with an accompanying diagnostic test, representing a more than 200% increase over the control group (Table 5, column 3). This increase in the share of ACTs sold with an accompanying test is due to the increase in testing that we discussed in Table 4. However, we need to look at columns 5 and 6 in this table to understand the aggregate decline in ACT uptake. These columns look at intervention effects on ACTs sold without an accompanying diagnostic test. We find an average treatment effect of a 20 percentage point decrease in ACT uptake without a diagnostic test, with the patient discount group having a -22 percentage point treatment effect, the pharmacy incentive group having a -16 percentage point treatment effect, and the combination of the patient discounts and pharmacy incentives

[18] Assuming a malaria positivity rate of 34%, derived from the random testing exercise done in the control group, 66% of these individuals are getting ACTs unnecessarily, or 57% of the total control group sample.

having a -18 percentage point treatment effect (again, no statistically significant difference across the three arms). The negative treatment effects we see here reflect the fact that patients were tested using rapid diagnostic tests (Table 4), a share of these patients received negative test results, and crucially, they elected not to purchase ACTs upon receiving that negative malaria diagnosis. Therefore, the overall decline in ACT uptake is driven by malaria negative patients not purchasing ACTs inappropriately.

Table 6 answers the question: how much of the effects on ACT uptake are due to the information provided by a diagnostic test vs. the ACT subsidy. These are not causal ITT estimates because we use (endogenous) information about testing uptake and test results to construct our comparison groups (including using malaria test positivity data to impute test results for the subset of the control group that got tested). However, they provide insights into the relative value of (a) information about one's own malaria status, and (b) an ACT subsidy/incentive on ACT uptake outcomes. The first two columns reproduce the main ITT effects on ACT uptake, but do so at the pharmacy-level. Incentive interventions reduce the share of ACTs sold by 24 percentage points on average (column 1), with patient discounts reducing by 27 percentage points and pharmacy incentives reducing by 22 percentage points (column 2). The rest of the table explores how much of this overall effect is due to information provided by the RDT versus the conditional financial incentive on ACTs. In columns 3 and 4, we see that conditional on the information provided by the test (positivity and negativity rates), the overall impact on ACT shares is diminished to about a 6 percentage point decrease overall (4 and 8 percentage point decrease for patient and provider incentives, respectively). Test negativity rate has a large negative impact on ACT sales, on average across treatment groups. Columns 5 and 6 interact positivity and negativity rates with treatment status, to explore how information affects outcomes by treatment arm. We find that the effect of information on ACT shares is entirely driven by the information effect in pharmacies that received incentive interventions (either patient or provider). So, the information provided by RDTs as a result of the incentive interventions is being acted upon in subsequent treatment

recommendations, with real impact on ACT uptake and sales. The ACT results we find are due in large part to this information effect, with the rest of the impact driven by the diagnosis-conditional pricing.

In order to understand the channels through which the demand- and supply-side interventions operated, we test the mechanisms of price pass-through and improved information. Data presented in Tables 7 and 8 are from Standardized Patient (SP) visit exit surveys. SPs conducted a total of 411 visits across 137 facilities in the study sample, with three different SPs visiting each facility. SPs followed a uniform script for how to present a suspected malaria case in a pharmacy setting: SPs were instructed to complain of fever, headache and joint pains in their opening statement and then provided additional information about their illness episode and health history if the pharmacist followed up with additional questions. SP visits provided a unique opportunity to assess the implementation fidelity and quality of care of the patient-provider interaction at study pharmacies. In column 1 of Table 7, we find evidence of partial incentive pass-through for rapid diagnostic tests in the patient discount group, but not in the supply-side incentive arms. The discount was reflected in a 43% price reduction for patients when the incentive was administered as a consumer subsidy (which implies a price elasticity of demand of 7.86).[19] This suggests that in the patient discount arm, the increase in testing uptake and improvements in treatment targeting can be explained by partial incentive pass-through on rapid diagnostic tests.

But, this mechanism does not appear to explain why we find similar effects in the two supply-side incentive arms. Table 8 presents results on the pharmacist-patient interaction using data collected from the SP exit surveys. We find no impact on the likelihood that the SP was offered a malaria diagnostic test, but the likelihood that SPs who went to control group pharmacies were offered a test was already quite high - 60%. This is much higher than the full sample, and is likely due to the fact that the SPs were instructed to present generalized symptoms and ask the pharmacist for their recommendation, rather

[19] Using 338% change in quantity, calculated from point estimates in Table 4

than begin by demanding antimalarials, which is also common practice in these settings. SPs report that between 37-45% of pharmacists in all arms, including the control group, are knowledgeable about malaria symptoms and treatment options, so there does not seem to be a gap in knowledge between providers as a result of the interventions. However, there is a difference in what providers actually do. We present results on the quality of counseling provided by pharmacists (Columns 5 and 6). In the control group, only 31% of providers provided comprehensive counseling on treatment options. On average, we see an 11 percentage point increase in the quality of information about treatment options given as a result of the interventions (Table 8, Column 5). This average effect is driven entirely by the supply-side incentive arms. When pharmacists are incentivized directly, they are 16 percentage points more likely than control group pharmacists to clearly explain treatment options to SPs. In the combined discount and incentives arm, we find a 14 percentage point increase. This suggests that when incentivized directly, pharmacists do change their behavior and provide more comprehensive counseling on testing and treatment options to suspected malaria patients. We do not find any treatment effects on time spent with the pharmacist (on average, 9-10 minutes across all arms), but find that patients in the provider arm are more likely to report that the provider showed them their individual test results as part of their counseling (columns 11-12). Taken together, this suggests that the information/counseling channel, rather than a price pass-through, is likely to explain the supply-side treatment effects we find in Tables 4 - 6.

3.2 Cost-effectiveness results

In order to compare the efficiency of each intervention, we conducted a cost-effectiveness analysis from the perspective of the program implementer (including only program costs) and from a societal perspective (including program cost and costs incurred by the care-seeking patient). We estimated incremental cost-effectiveness ratios (ICERs) in terms of cost per patient obtaining ACTs appropriately, defined as being malaria positive. We used

a time horizon equal to the duration of the intervention period (8 months) and included all malaria patients who sought care at study pharmacies for this analysis. All methods, parameter inputs and assumptions are described in the methods section and Appendix 4.

Table 9 presents the incremental benefits and ICERs from the implementer perspective (top panel) and from the societal perspective (bottom panel). Within each panel, we present incremental gains and ICERs for each intervention (patient subsidies, pharmacy incentives, or combined) relative to the control group, as this is the most policy-relevant benchmark when deciding amongst these possible intervention approaches. The control group resulted in 73 appropriately targeted ACTs. Patient subsidies resulted in 180 additional appropriately targeted ACTs at a cost of $14.30/patient, pharmacy incentives resulted in an additional 258 patients treated appropriately at a cost of $12.87/patient, and the combined approach resulted in an additional 165 patients treated appropriately at a cost of $22.72/patient (all from Panel A, Table 9).

From a societal perspective (Panel B, Table 9), we find that patient subsidies result in an additional 180 patients treated appropriately with ACTs at a cost of -$57.60/patient compared to the control group, which is cost-saving. We find that pharmacy incentives are even more cost saving: compared to the control group, this intervention leads to 258 additional patients treated appropriately with ACTs at a cost of -$142.14/patient. And finally, the combined intervention leads to an additional 165 ACTs targeted appropriately compared to the control group, at a cost of $35.92/patient. These cost-effectiveness estimates likely understate the true benefits of these interventions because they do not incorporate the benefits incurred by malaria negative patients foregoing unnecessary antimalarials, and thus not contributing to increased likelihood of drug-resistant mosquito strains, which are a social cost.

4 Discussion

We examine the effects and mechanisms of demand- and supply-side incentive programs designed to improve malaria case management in a cluster-randomized control trial in Kenya. The experimental treatments provided financial incentives to patients, pharmacists, or both for rapid diagnostic tests and ACTs conditional on testing positive for malaria and were implemented in private sector pharmacies in thirteen malaria-prone counties. Pharmacies play a significant role in malaria case management in Kenya, and this study provides some of the first evidence of how interventions designed and implemented in pharmacy settings can change prescribing/purchase behavior with implications for illness management.

We find encouraging results of the demand- and supply-side incentives on both testing and treatment targeting. Overall, the incentives interventions increased RDT use substantially in a setting with very low baseline testing levels. On average, patients who sought care in treatment pharmacies were 25 percentage points more likely to receive a formal malaria diagnosis prior to purchasing treatment for suspected malaria. This represents a more than 300% increase over the control group. Incentive interventions were also effective encouraging appropriate use of antimalarials. We find an overall 14 percentage point decrease in the use of ACTs as a result of the treatment, and this is due to malaria negative patients opting out of purchasing unnecessary antimalarials. For patients who test positive, we find that they are appropriately nudged to take ACTs, consistent with their diagnostic test result. Interestingly, we find statistically indistinguishable effects of the demand-side and supply-side treatment arms, suggesting that incentives yield similar outcomes whether they are provided directly to patients or they are provided to pharmacists.

We explore mechanisms through which the incentive interventions worked in order to contextualize the main findings. We find that the patient subsidies for RDTs resulted in significantly lower prices being paid by patients (43% reduction in price). However, we find no evidence of pass-through of the RDT incentive in either of the two supply-side arms, and no evidence of price pass-through on ACT prices in any of the three treatment arms. Instead,

we find evidence that in the supply-side incentive arms, pharmacists explained diagnosis and treatment options more comprehensively to their patients. Improved, individualized health information appears to be the channel through which the supply-side incentives resulted in the overall changes in RDT and ACT use seen in the main results. In sum, the demand subsidies induced more patients to purchase RDTs that provided accurate illness status information, which led to more appropriate use of ACTs. And, the supply incentives led pharmacists to provide more detailed diagnosis counseling and treatment recommendations, yielding similar results.

This study adds to the literature on how individualized health information and financial incentives can be combined to change health behavior. Critically, this study builds on several other field experiments that look at the effectiveness of incentives in improving uptake of malaria diagnostic testing and treatment targeting. Cohen, Dupas and Schaner find that subsidizing ACTs leads to significant increases in ACT uptake, but that the increased demand comes at a cost: only about half of the subsidized ACTs are taken by malaria-positive individuals (J. Cohen, Pascaline Dupas, and Schaner 2015). They find that a rapid test subsidy also increases uptake of testing, but does little to improve testing targeting. Subsequent work by Prudhomme O'Meara and colleagues in Kenya finds that providing free rapid tests increases testing uptake, and providing subsidies for ACTs when patients test positive increases the use of ACTs when malaria positive (O'Meara, Menya, et al. 2018). We find results on testing uptake that are consistent with both of these studies: incentivizing rapid tests does increase usage significantly. However, we additionally find that diagnosis conditional incentives for ACTs improve treatment targeting. One key difference between this study and those that came before it is that these incentive interventions are entirely administered in pharmacies and by pharamcists, rather than using community health workers to test and refer patients to retail outlets to purchase treatments.

This study contributes to our understanding of how incentives targeted at the demand-side or the supply-side can affect health decision-making by comparing demand- and supply-

side incentive approaches directly to each other. The fact that we find no significant differences in testing uptake or treatment targeting between demand and supply approaches suggests that targeting incentives to either patients or providers is effective at improving malaria case management in a pharmacy setting. This is interesting from a policy and implementation perspective, because it provides some evidence that incentive programs can be applied at the level that is most operationally-feasible, with limited impact on overall effectiveness in terms of end-user outcomes.

Finally, this study provides evidence on how pharmacists make decisions, and provides cost-effectiveness estimates that can be used by decision-makers to compare this intervention to others aimed at improving malaria care. Given that pharmacies play an important role in health care provision in many low- and middle-income countries, understanding pharmacist motivations and how interventions aimed at improving quality of care work in a pharmacy context is a crucial policy relevant question. The fact that we find improvements in malaria case management suggests that pharmacy-level interventions is one promising avenue to improve quality of care.

Overall, demand and supply incentives are both effective at encouraging uptake of malaria RDTs and improving treatment targeting in a pharmacy setting, which is characterized by low levels of diagnostic testing and high levels of antimalarial overuse. Incentives may operate through different channels, depending on whether they are given to patients or providers, but yield similar outcomes in terms of quality of care. Demand incentives translate into price reductions for patients for RDTs, and supply incentives induce pharmacists to provide more comprehensive counseling. This research demonstrates that incentives targeted to either patients or pharmacists can lead to improvements in malaria case management, and that having pharmacy-level programs aimed at improving malaria care has the potential to improve outcomes.

References

[1] Tashrik Ahmed et al. "Incentivizing quantity and quality of care: evidence from an impact evaluation of performance-based financing in the health sector in Tajikistan". In: *Economic Development and Cultural Change* 71.2 (2023), pp. 000–000.

[2] Evelyn K Ansah et al. "Rapid testing for malaria in settings where microscopy is available and peripheral clinics where only presumptive treatment is available: a randomised controlled trial in Ghana". In: *Bmj* 340 (2010).

[3] Kenneth J Arrow. "Th1e american". In: *The American Economic Review* 53.5 (1963), pp. 941–973.

[4] Kenneth J Arrow. "Uncertainty and the welfare economics of medical care". In: *Uncertainty in economics*. Elsevier, 1978, pp. 345–375.

[5] Paulin Basinga et al. "Effect on maternal and child health services in Rwanda of payment to primary health-care providers for performance: an impact evaluation". en. In: *The Lancet* 377.9775 (Apr. 2011), pp. 1421–1428. ISSN: 0140-6736. DOI: 10.1016/S0140-6736(11)60177-3. URL: http://www.sciencedirect.com/science/article/pii/S0140673611601773 (visited on 01/26/2020).

[6] Deron C Burton et al. "Healthcare-seeking behaviour for common infectious disease-related illnesses in rural Kenya: a community-based house-to-house survey". In: *Journal of health, population, and nutrition* 29.1 (2011), p. 61.

[7] Meghan Busse, Jorge Silva-Risso, and Florian Zettelmeyer. "$1,000 cash back: The pass-through of auto manufacturer promotions". In: *American Economic Review* 96.4 (2006), pp. 1253–1270.

[8] Stephen M Campbell et al. "Effects of pay for performance on the quality of primary care in England". In: *New England Journal of Medicine* 361.4 (2009), pp. 368–378.

[9] Jessica Cohen, Pascaline Dupas, and Simone Schaner. "Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial". en. In: *American Economic Review* 105.2 (Feb. 2015), pp. 609–645. ISSN: 0002-8282. DOI: 10.1257/aer.20130267. URL: https://www.aeaweb.org/articles?id=10.1257/aer.20130267 (visited on 11/21/2019).

[10] Jessica L Cohen et al. "Do price subsidies on artemisinin combination therapy for malaria increase household use?: evidence from a repeated cross-sectional study in remote regions of Tanzania". In: *PloS one* 8.7 (2013).

[11] Janet Currie, Wanchuan Lin, and Juanjuan Meng. "Addressing antibiotic abuse in China: an experimental audit study". In: *Journal of development economics* 110 (2014), pp. 39–51. ISSN: 0304-3878.

[12] David M Cutler and Richard J Zeckhauser. "The anatomy of health insurance". In: *Handbook of health economics*. Vol. 1. Elsevier, 2000, pp. 563–643.

[13] Jishnu Das and Jeffrey Hammer. "Quality of primary care in low-income countries: facts and economics". In: *Annu. Rev. Econ.* 6.1 (2014), pp. 525–553.

[14] Centers for Disease Control and Prevention. *CDC Malaria Support in Kenya*. 2018. URL: https://www.cdc.gov/malaria/malaria_worldwide/cdc_activities/kenya.html.

[15] William H Dow, Justin S White, and Stefano Bertozzi. "Incentivizing health care utilization and health outcomes". In: *World Scientific Handbook of Global Health Economics and Public Policy: Volume 1: The Economics of Health and Health Systems*. World Scientific, 2016, pp. 421–451.

[16] P. Dupas and E. Miguel. "Chapter 1 - Impacts and Determinants of Health Levels in Low-Income Countries". en. In: *Handbook of Economic Field Experiments*. Ed. by Abhijit Vinayak Banerjee and Esther Duflo. Vol. 2. Handbook of Economic Field Experiments. North-Holland, Jan. 2017, pp. 3–93. DOI: 10.1016/bs.hefe.2016.09.003. URL: http://www.sciencedirect.com/science/article/pii/S2214658X16300113 (visited on 01/26/2020).

[17] Pascaline Dupas. "Health behavior in developing countries". In: *Annu. Rev. Econ.* 3.1 (2011), pp. 425–449. ISSN: 1941-1383.

[18] Pascaline Dupas. "Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment". In: *Econometrica* 82.1 (2014). Publisher: Wiley Online Library, pp. 197–228. ISSN: 0012-9682.

[19] Katherine E Fleming-Dutra et al. "Prevalence of inappropriate antibiotic prescriptions among US ambulatory care visits, 2010-2011". In: *Jama* 315.17 (2016), pp. 1864–1873.

[20] Paul Gertler, Paula Giovagnoli, and Sebastian Martinez. *Rewarding Provider Performance to Enable a Healthy Start to Life: Evidence from Argentina's Plan Nacer*. 2014. URL: https://openknowledge.worldbank.org/bitstream/handle/10986/18801/WPS6884.txt (visited on 11/25/2019).

[21] Erick Gong. "HIV testing and risky sexual behaviour". In: *The Economic Journal* 125.582 (2015), pp. 32–60.

[22] U.S. Presidents Malaria Initiative. *U.S. Presidents Malaria Initiative Kenya Malaria Operational Plan FY 2020*. 2021.

[23] Carolina Lopez, Anja Sautmann, and Simone Schaner. "Does Patient Demand Contribute to the Overuse of Prescription Drugs?" In: (2020).

[24] Xiaochen Ma et al. "Effect of providing free glasses on childrens educational outcomes in China: cluster randomized controlled trial". In: *Bmj* 349 (2014), g5740. ISSN: 1756-1833.

[25] Elisa M Maffioli et al. "Can Individuals Beliefs Help Us Understand Non-Adherence to Malaria Test Results - Evidence from Rural Kenya". In: *Economic Research Initiatives at Duke (ERID) Working Paper* 243 (2019).

[26] Moureen Maraka et al. "A seven-year surveillance of epidemiology of malaria reveals travel and gender are the key drivers of dispersion of drug resistant genotypes in Kenya". In: *PeerJ* 8 (2020), e8082.

[27] Anthony K Mbonye et al. "Treatment of fevers prior to introducing rapid diagnostic tests for malaria in registered drug shops in Uganda". In: *Malaria journal* 12 (2013), pp. 1–10.

[28] Thomas G McGuire. "Physician agency". In: *Handbook of health economics* 1 (2000), pp. 461–536.

[29] Jennifer Meredith et al. "Keeping the doctor away: experimental evidence on investment in preventative health products". In: *Journal of Development Economics* 105 (2013), pp. 196–210. ISSN: 0304-3878.

[30] Grant Miller and Kimberly Singer Babiarz. "Pay-for-performance incentives in low-and middle-income country health programs". In: (2013).

[31] Anne Musuva et al. "The malaria testing and treatment landscape in Kenya: results from a nationally representative survey among the public and private sector in 2016". In: *Malaria journal* 16.1 (2017), pp. 1–13.

[32] Wendy Prudhomme O'Meara, Diana Menya, et al. "Improving rational use of ACTs through diagnosis-dependent subsidies: Evidence from a cluster-randomized controlled trial in western Kenya". en. In: *PLOS Medicine* 15.7 (July 2018), e1002607. ISSN: 1549-1676. DOI: 10.1371/journal.pmed.1002607. URL: https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1002607 (visited on 11/21/2019).

[33] Wendy Prudhomme O'Meara, Manoj Mohanan, et al. "Assessing the independent and combined effects of subsidies for antimalarials and rapid diagnostic testing on fever management decisions in the retail sector: results from a factorial randomised trial in western Kenya". en. In: *BMJ Global Health* 1.2 (Sept. 2016). ISSN: 2059-7908. DOI: 10.1136/bmjgh-2016-000101. URL: https://gh.bmj.com/content/1/2/e000101 (visited on 11/21/2019).

[34] Mark Pauly. "Doctors and Their Workshops: Economic Models of Physician Behavior". In: *Doctors and Their Workshops: Economic Models of Physician Behavior*. University of Chicago Press. 1980, pp. 119–122.

[35] John W Peabody et al. "The impact of performance incentives on child health outcomes: results from a cluster randomized controlled trial in the Philippines". In: *Health Policy and Planning* 29.5 (2014), pp. 615–621.

[36] Michael J Podgursky and Matthew G Springer. "Teacher performance pay: A review". In: *Journal of policy analysis and management* 26.4 (2007), pp. 909–949.

[37] Canice Prendergast. "The provision of incentives in firms". In: *Journal of economic literature* 37.1 (1999), pp. 7–63.

[38] Margaret Whitehead, Göran Dahlgren, and Timothy Evans. "Equity and health sector reforms: can low-income countries escape the medical poverty trap?" In: *The Lancet* 358.9284 (2001), pp. 833–836.

[39] WHO. *WHO Guidelines for malaria*. Licence: CC BY-NC-SA 3.0 IGO. 2021.

[40] Sophie Witter et al. "Paying for performance to improve the delivery of health interventions in low-and middle-income countries". In: *Cochrane database of systematic reviews* 2 (2012).

[41] Aaron M Woolsey et al. "Incentivizing appropriate malaria case management in the private sector: a study protocol for two linked cluster randomized controlled trials to evaluate provider-and client-focused interventions in western Kenya and Lagos, Nigeria". In: *Implementation Science* 16.1 (2021), pp. 1–11.

[42] World Health Organization. *World malaria report 2018*. en. OCLC: 1088512397. 2018. ISBN: 978-92-4-156565-3.

[43] Winnie Yip et al. "Capitation combined with pay-for-performance improves antibiotic prescribing practices in rural China". In: *Health affairs* 33.3 (2014), pp. 502–510.

Tables

Table 1: Study timeline (Back: 2.4)

Jun-Dec '21	**Experiment launch**: baseline pharmacy survey with 233 pharmacy owners and staff from all 140 sites; staggered onboarding of 140 pharmacies to intervention and study
Aug '21-Feb '22	**Monitoring**: implementation team monitors intervention implementation through regular outreach calls and random site visits; ongoing administrative data collection through digital platform
Oct '21-Jan '22	**Patient exit survey**: survey of random sample of 1654 adult clients who seek care for malaria-like symptoms
Dec '21-Feb '22	**Standardized patient visits**: 412 mystery shopper visits by enumerators presenting as suspected malaria patients, to obtain data on patient-pharmacist interaction, implementation fidelity, and quality of care
Jan-Feb '22	**Control group testing**: testing of random subset of 230 pharmacy clients at control group sites to obtain test positivity rate
Mar '22	**Pharmacy endline survey**: survey of all pharmacy staff and owners at conclusion of the data collection period

Table 2: Baseline Balance Between Treatment Arms, Administrative Data (Back: 2.6)

Variable	(1) Control	(2) T1	(3) T2	(4) T3	(5) T1-T2	(6) T3-T1	(7) T2-T3
Number of months active on digital sales management tool	10.14	9.06	5.37*	8.11	3.69+	-0.94	-2.74
	(10.48)	(9.42)	(8.02)	(10.02)	(0.08)	(0.69)	(0.21)
Below median baseline malaria sales	0.37	0.46	0.37	0.46	0.09	-0.00	-0.09
	(0.49)	(0.51)	(0.49)	(0.51)	(0.47)	(1.00)	(0.47)
Average monthly malaria sales, 2019-2020	64.80	54.97	53.12	43.58+	1.85	-11.39	9.55
	(60.34)	(53.99)	(50.49)	(39.98)	(0.88)	(0.32)	(0.38)
Average monthly ACT sales, 2019-2020	52.84	46.89	47.64	38.60	-0.75	-8.29	9.04
	(39.27)	(50.21)	(48.16)	(38.46)	(0.95)	(0.44)	(0.39)
Average monthly rapid test sales, 2019-2020	4.30	7.56	4.61	3.53	2.95	-4.03+	1.08
	(5.34)	(11.35)	(9.17)	(4.06)	(0.24)	(0.05)	(0.53)
Site participated in earlier pilot phase	0.17	0.20	0.17	0.09	0.03	-0.11	0.09
	(0.38)	(0.41)	(0.38)	(0.28)	(0.76)	(0.18)	(0.29)
Site is in an urban area	0.20	0.29	0.40+	0.34	-0.11	0.06	0.06
	(0.41)	(0.46)	(0.50)	(0.48)	(0.32)	(0.61)	(0.63)
Site is in a malaria endemic county	0.89	0.77	0.80	0.91	-0.03	0.14	-0.11
	(0.32)	(0.43)	(0.41)	(0.28)	(0.77)	(0.10)	(0.18)
Site is not a clinic	0.71	0.83	0.83	0.83	0.00	-0.00	0.00
	(0.46)	(0.38)	(0.38)	(0.38)	(1.00)	(1.00)	(1.00)
Observations	35	35	35	35	70	70	70

Significance stars are from pairwise comparisons with the control group: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Differences between treatment arms are in columns 5-7 (p-values in parentheses)

Multinomial logit test for joint orthogonality produces p-value from χ^2-test of 0.46

Table 3: Baseline Balance Between Treatment Arms, Pharmacy Survey Data (Back: 2.6)

Variable	(1) Control	(2) T1	(3) T2	(4) T3	(5) T1-T2	(6) T3-T1	(7) T2-T3
Percentage of pharmacy staff who are female	0.44	0.35	0.51	0.44	-0.16+	0.09	0.07
	(0.42)	(0.41)	(0.39)	(0.42)	(0.10)	(0.36)	(0.46)
Age of pharmacy owner	37.43	35.37	36.40	35.71	-1.03	0.34	0.69
	(5.28)	(7.74)	(7.14)	(8.08)	(0.57)	(0.86)	(0.71)
Average age of pharmacy staff	29.37	29.37	28.94	29.29	0.43	-0.09	-0.34
	(5.32)	(4.15)	(5.80)	(5.11)	(0.72)	(0.94)	(0.79)
Owner is female	0.36	0.16*	0.17+	0.17+	-0.01	0.01	0.00
	(0.48)	(0.36)	(0.38)	(0.36)	(0.87)	(0.87)	(1.00)
Number of pharmacy staff	1.54	1.54	1.49	1.40	0.06	-0.14	0.09
	(0.51)	(0.56)	(0.51)	(0.50)	(0.66)	(0.26)	(0.48)
Observations	35	35	35	35	70	70	70

Significance stars are from pairwise comparisons with the control group: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Differences between treatment arms are in columns 5-7 (p-values in parentheses)

Multinomial logit test for joint orthogonality produces p-value from χ^2-test of 0.46

Table 4: Impact on rapid test uptake, adjusted logistic regression (Back: 3.1)

	Rapid test uptake	
	(1)	(2)
Pooled treatment	.25**	
	(0.051)	
Patient discount		.267*
(γ_{T1})		(0.106)
Pharmacy incentive		.194**
(γ_{T2})		(0.065)
Patient discount and		.201**
pharmacy incentive (γ_{T3})		(0.054)
Control mean	0.081	0.081
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2} \neq \gamma_{T3}$)		0.827
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2}$)		0.540
Wald test p-val ($\gamma_{T1} \neq \gamma_{T3}$)		0.606
Wald test p-val ($\gamma_{T2} \neq \gamma_{T3}$)		0.940
N	51441	51441

Standard errors are clustered at the facility level
Controls: months active on platform, baseline malaria sales,
female owner, strata and calendar month FE
Wald test comparisons of difference in marginal effects (γ)
between treatment arms
Denominator is all patients that purchased malaria product during study period
45 obs dropped b/c multicollinearity (strata 11)
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 5: Impact on ACT uptake and treatment targeting, adjusted logistic regression (Back: 3.1)

	ACT uptake		ACT uptake with test		ACT uptake without test	
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled treatment	-.139**		.0748*		-.197**	
	(0.049)		(0.034)		(0.060)	
Patient discount (γ_{T1})		-.145*		.072		-.218*
		(0.069)		(0.050)		(0.110)
Pharmacy incentive (γ_{T2})		-.0892+		.0769+		-.161*
		(0.050)		(0.045)		(0.075)
Patient discount and pharmacy incentive (γ_{T3})		-.136**		.0511+		-.183**
		(0.047)		(0.029)		(0.068)
Control mean	0.867	0.867	0.057	0.057	0.809	0.809
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2} \neq \gamma_{T3}$)		.602		0.839		0.881
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2}$)		0.433		0.938		0.629
Wald test p-val ($\gamma_{T1} \neq \gamma_{T3}$)		0.904		0.710		0.782
Wald test p-val ($\gamma_{T2} \neq \gamma_{T3}$)		0.394		0.587		0.802
N	51486	51486	51486	51486	51441	51441

Standard errors are clustered at the facility level
Controls: months active on platform, baseline malaria sales,
female owner, strata and calendar month FE
Wald test comparisons of difference in marginal effects (γ) between treatment arms
Denominator is all patients that purchased malaria product during study period
Outcome 3: 45 obs dropped b/c multicollinearity (strata 11)
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 6: Impact on ACT sales by test result, pharmacy-level analysis (Back: 3.1)

	Share of ACTs sold Pharmacy-level					
	(1)	(2)	(3)	(4)	(5)	(6)
Pooled treatment	-.235**		-.0643+		.0349	
	(0.054)		(0.038)		(0.047)	
Patient discount		-.27**		-.0377		.0643
		(0.064)		(0.045)		(0.065)
Pharmacy incentive		-.217**		-.0762+		.0245
		(0.057)		(0.039)		(0.050)
Test positivity rate			-.108	-.0948	.0917	.0986
			(0.091)	(0.092)	(0.733)	(0.736)
Test negativity rate			-.756**	-.77**	-.101	-.102
			(0.058)	(0.059)	(0.189)	(0.190)
Pooled × Positivity rate					-.192	
					(0.736)	
Pooled × Negativity rate					-.711**	
					(0.196)	
Patient discount × Positivity rate						-.166
						(0.760)
Pharmacy incentive × Positivity rate						-.186
						(0.741)
Patient discount × Negativity rate						-.72**
						(0.212)
Pharmacy incentive × Negativity rate						-.732**
						(0.202)
Control mean	0.891	0.891	0.891	0.891	0.891	0.891
Positivity rate, overall			0.127	0.127	0.127	0.127
Positivity rate, Patient discount			0.10	0.10	0.10	0.10
Positivity rate, Pharmacy incentive			0.141	0.141	0.141	0.141
Negativity rate, overall			0.342	0.342	0.342	0.342
Negativity rate, Patient discount			0.422	0.422	0.422	0.422
Negativity rate, Pharmacy incentive			0.302	0.302	0.302	0.302
N	132	132	132	132	132	132

Controls: months active on platform, baseline malaria sales, female owner
Wald test comparisons were conducted of difference in marginal effects (γ) between patient and provider treatment arms. No significant differences were found.
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 7: Evidence of incentive pass-through, SP visits (Back: 3.1)

	Log price of rapid test
	(1)
Patient discount	-.427*
	(0.174)
Pharmacy incentive	-.0273
	(0.094)
Patient discount and pharmacy incentive	-.0895
	(0.095)
Control group mean (KSH)	48.952
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2} \neq \gamma_{T3}$)	<0.001
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2}$)	<0.001
Wald test p-val ($\gamma_{T1} \neq \gamma_{T3}$)	<0.001
Wald test p-val ($\gamma_{T2} \neq \gamma_{T3}$)	<0.001
N	137

Wald test comparisons of difference in marginal effects (γ) between treatment arms
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 8: Evidence on quality of care, SP visits (Back: 3.1)

	Malaria test offered		Pharmacist was knowledgeable		Pharmacist expained treatment		Minutes spent with pharmacist		Saw malaria test results (full sample)		Saw malaria test results (tested sample)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Pooled treatment	.0361		.0663		.111*		.84		.0721		.101	
	(0.066)		(0.062)		(0.056)		(0.974)		(0.058)		(0.073)	
Patient discount		.0805		.0836		.0353		.795		.0583		.0442
		(0.070)		(0.081)		(0.069)		(1.157)		(0.068)		(0.091)
Pharmacy incentive		.0214		.0834		.162*		.624		.124		.187*
		(0.084)		(0.079)		(0.069)		(1.120)		(0.078)		(0.089)
Patient discount and pharmacy incentive		.00572		.0303		.135+		1.11		.032		.0659
		(0.084)		(0.073)		(0.069)		(1.308)		(0.072)		(0.088)
Control mean	0.600	0.600	0.371	0.371	0.314	0.314	8.971	8.971	0.305	0.305	0.508	0.508
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2} \neq \gamma_{T3}$)		.517		.729		.169		.926		.527		.251
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2}$)		.415		.998		.075		.873		.408		.133
Wald test p-val ($\gamma_{T1} \neq \gamma_{T3}$)		.312		.508		.157		.802		.721		.813
Wald test p-val ($\gamma_{T2} \neq \gamma_{T3}$)		.857		.501		.695		.695		.267		.171
N	411	411	411	411	411	411	411	411	411	411	259	259

Standard errors are clustered at the facility level

Regressions control for mystery client fixed effect

F test comparisons of difference in effects between treatment arms

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table 9: Incremental Benefits and ICERs (Back: 3.2)

Incremental benefits and ICERs, compared to control group

	Number of malaria positive patients treated with ACTs*	Incremental appropriately treated	ICER Cost / patient appropriately treated
		Implementer perspective	
T1 vs. C	238	180	$14.30
T2 vs. C	253	258	$12.87
T3 vs. C	331	165	$22.72
		Societal perspective	
T1 vs. C	238	180	-$57.60
T2 vs. C	253	258	-$142.14
T3 vs. C	331	165	$35.92

*73 malaria positive patients treated with ACTs in the control group

Figures

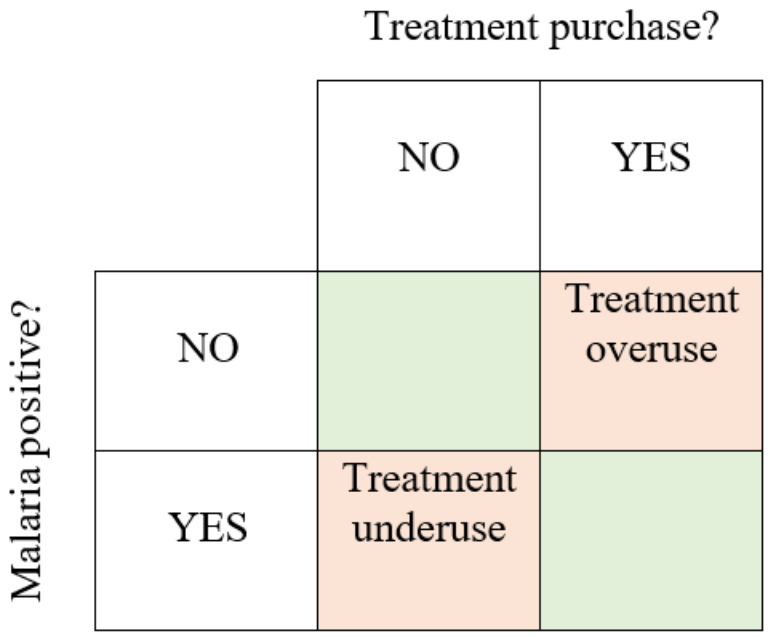

Figure 1: Types of errors (Back: 2)

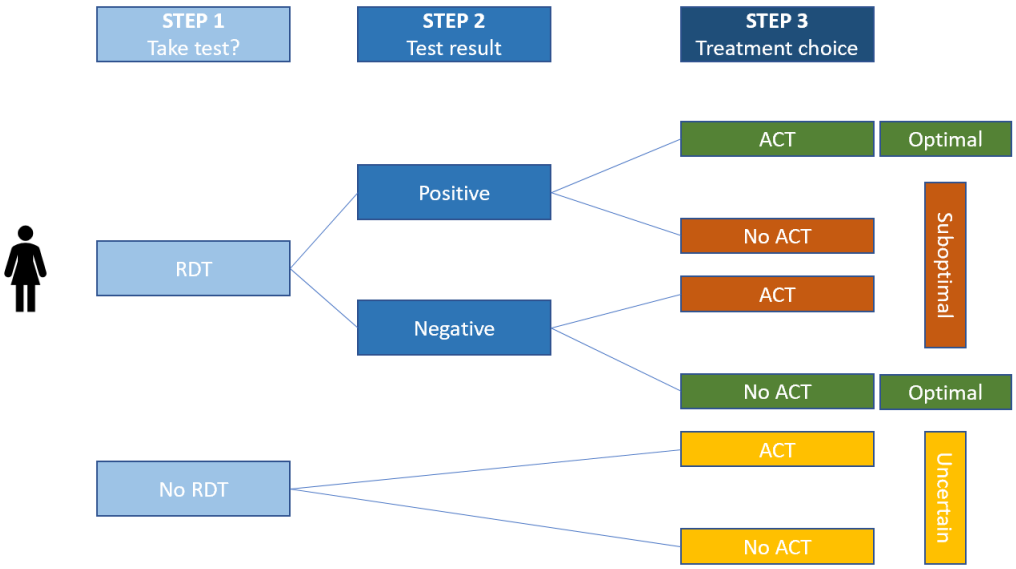

Figure 2: Patient decision to test and treat (Back: 2.1)

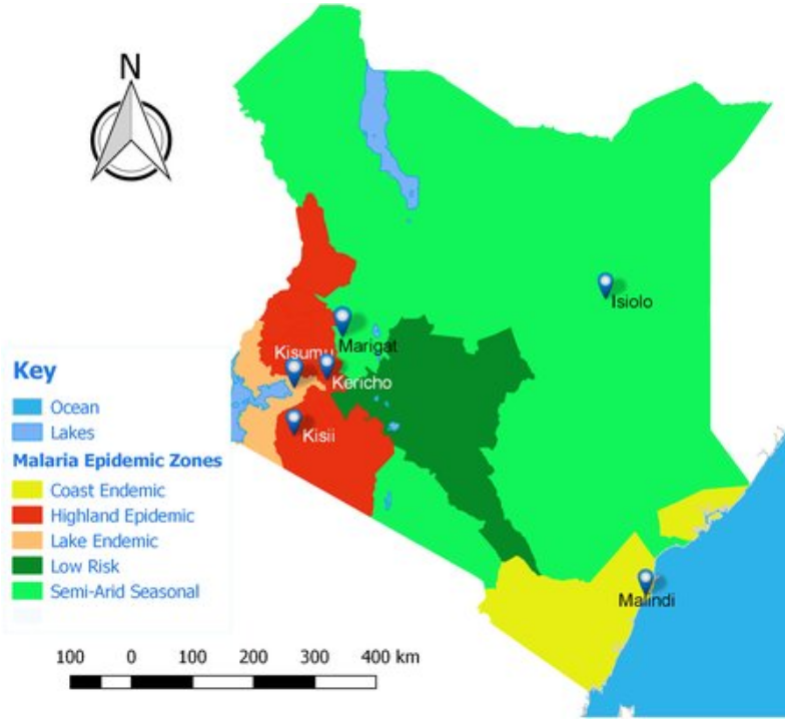

Figure 3: Malaria zones in Kenya, source: Maraka et al. 2020 (Back: **??**)

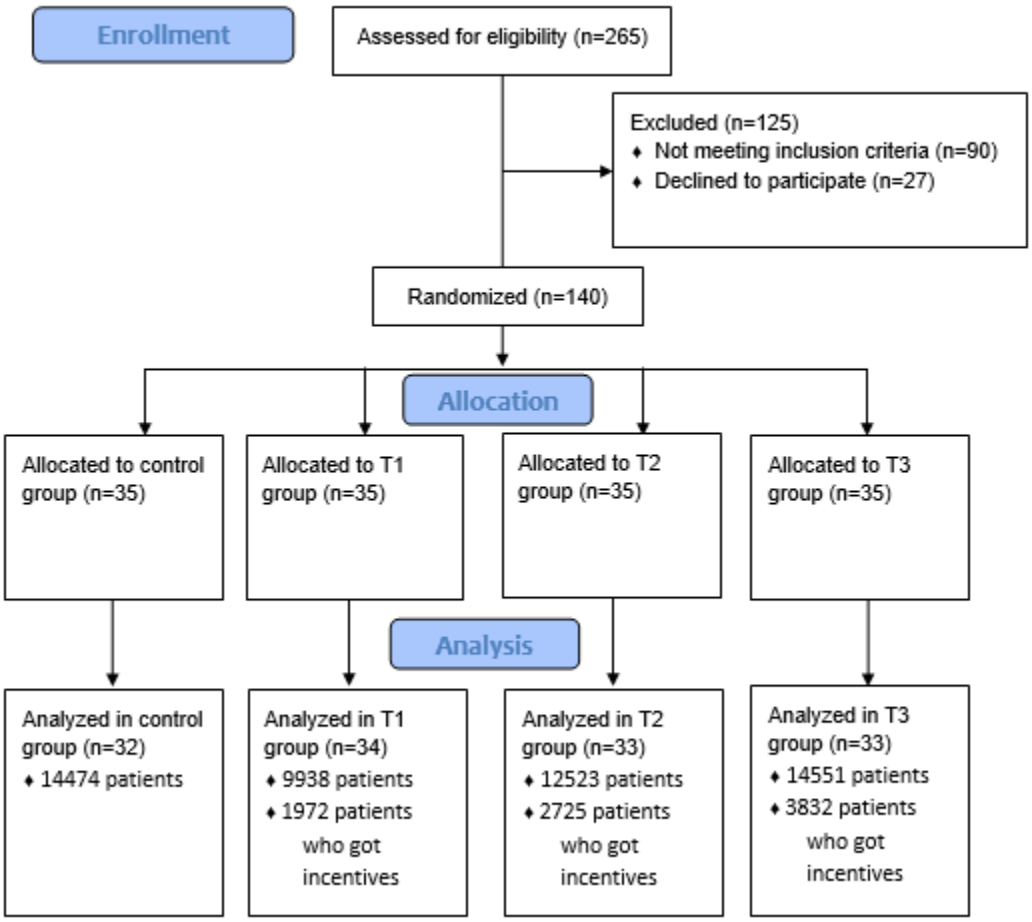

Figure 4: Study flow diagram (Back: 2.2)

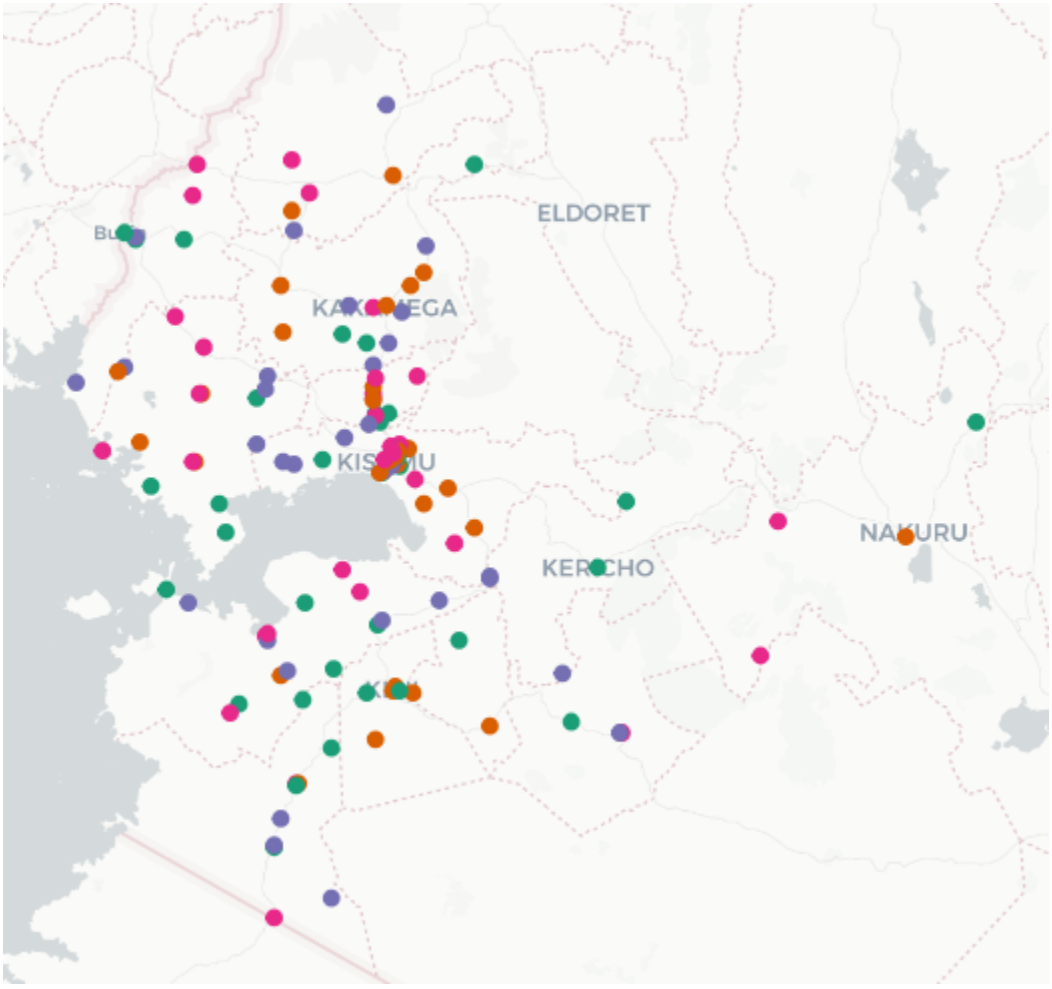

Figure 5: Map of study sites (Back: 2.3)

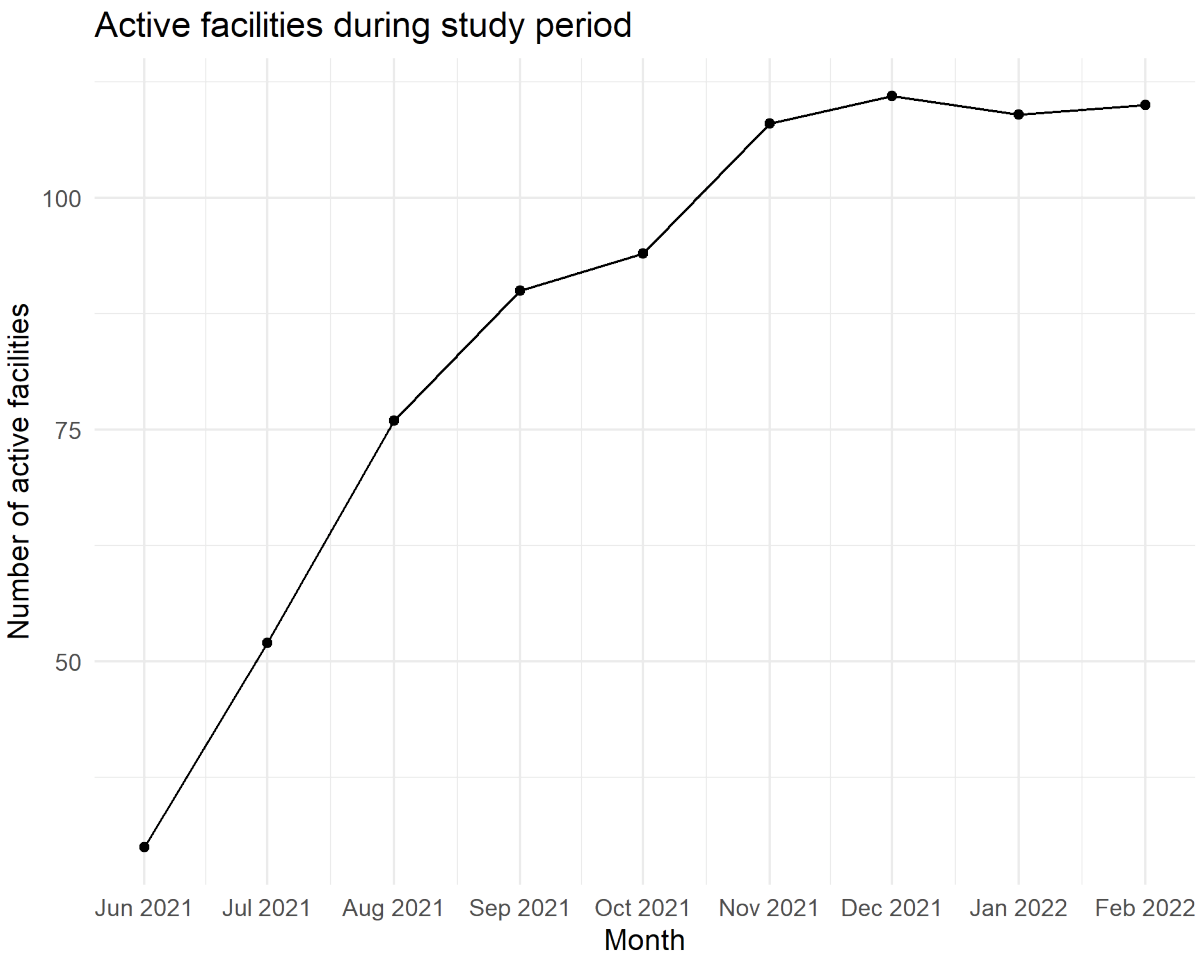

Figure 6: Active facilities during study period (all transactions) (Back: 2.6)

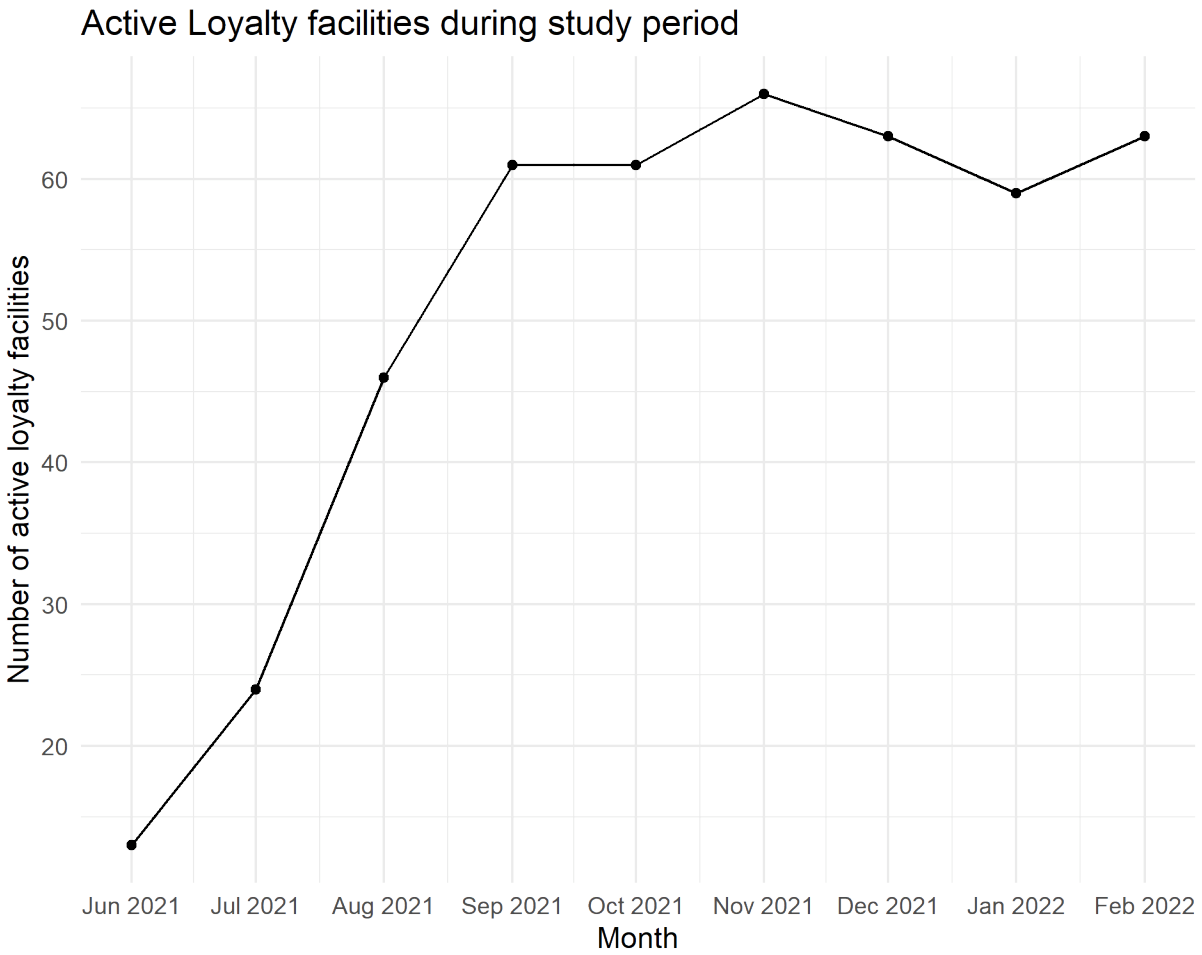

Figure 7: Active treatment facilities during study period (incentivized transactions) (Back: 2.6)

Appendix A. Cost-effectiveness Analysis Supplement

4.1 CEA Methods

Benefits are measured as patients who take ACTs appropriately (are malaria positive), therefore only patients who are malaria positive contribute to the benefits. To estimate the number of patients who get ACTs appropriately in each of the intervention arms, we use the following equation:

$$\text{Beneficiaries}_t = Pr(ACT|positive)_t \times ACT_t$$

where $Pr(ACT|positive)_t$ is the probability of purchasing an ACT conditional on being malaria positive, for each intervention arm t, and ACT_t is the number of patients in intervention arm t who purchase ACTs. This is the share of patients who purchase ACTs,[20] multiplied by a hypothetical cohort of 10,000 patients. $Pr(ACT|positive)_t$ can be further expanded into a component that applies to patients who were tested for malaria and one that applies to patients who were not tested:

$$\begin{aligned} Pr(ACT|positive)_t = {} & Pr(ACT|positive\&tested)_t Pr(positive|tested)_t Pr(tested)_t + \\ & Pr(ACT|positive\&untested)_t Pr(positive|untested)_t Pr(untested)_t \end{aligned}$$

Each of these probabilities can be found from the parameters that are measured through the experimental design and data collection activities. $Pr(ACT|positive\&tested)$ is directly estimated from the administrative data in the treatment groups, for patients accessing incentivized tests and treatments. In the control group, this probability is estimated using the control group mean from column 4 of Table 5 (0.057) multiplied by the control group $Pr(positive|tested)$. $Pr(positive|tested)$ is obtained from administrative pharmacy data in all four arms. In the control group, this comes from aggregate reported test positivity rates from 2547 tests done in 10 control group sites that conducted testing between January-February 2022 and kept records. In the treatment groups, this comes from the administrative data collected through the study on individual test results, for patients who tested through the intervention. $Pr(tested)$ is directly estimated from the administrative data in all four arms, and is the treatment arm specific mean in column 2 of Table 4. $Pr(ACT|positive\&untested)$ is estimated for all four arms and is the treatment group specific means of $Pr(ACT|untested)$ from column 6 in Table 5

[20] Obtained from intervention group specific means from Table 5, column 2.

multiplied by $Pr(positive|untested)$. $Pr(positive|untested)$ is estimated in the control group using data collected from the lab tech activity which tested a random subset of 230 patients who purchased antimalarials for a suspected illness at 28 control group sites but did not get tested prior between January-February 2022. In the treatment groups, $Pr(positive|untested) = Pr(positive) - Pr(positive|tested)$. $Pr(positive)$ is the unselected (for testing) malaria positivity rate, and is obtained from the control group testing data ($Pr(positive|tested) + Pr(positive|untested)$), and $Pr(positive|tested)$ is directly obtained from the administrative transaction data for patients who purchased incentivized tests.

The inputs needed to calculate the number of beneficiaries in each intervention arm can be found in Appendix Table A1. We estimate the program benefits for each intervention using these parameters and compare them to the status quo standard of care, as well as to the next best alternative. For details on the sources of each parameter input for the benefits, please see Appendix Tables A2 and A3. For details on formulas used to calculate the benefits estimates, please see Appendix Table A4.

The costs can be broken down into direct costs of running the incentives program, the direct costs of over-treating malaria negative patients, and other non-programmatic costs to patients of participating in the program. To estimate these costs, we use the following equation:

$$\text{TotalCost}_t = c_t\text{Patients}_t + \text{CostOverTx}_t \times \text{PatientsOverTx}_t + \text{CostTime}_t$$

where $t \in (0, 1, 2, 3)$ is one of the three treatment arms or control group, c is the cost of administering the incentive interventions, $Patients$ is the number of patients who purchased an incentivized product, $CostOverTx$ is the cost of over-treating malaria negative patients with antimalarials, $PatientsOverTx$ is the number of patients who were treated unnecessarily, and $CostTime$ is the time cost to patients of obtaining care for their malaria symptoms in the pharmacy setting.

In order to estimate the costs of over-treating malaria negative patients, we first estimate the average cost of treatment for patients who did not get tested for malaria and the average cost of treatment for patients who did get tested for malaria. These cost estimates are directly observed from the administrative data, and we have estimates for each of these out of pocket costs for each of my intervention arms. Then we also observe the number of untested patients and number of tested patients in each treatment arm, again from the administrative data. We estimate the likelihood of being malaria negative condition on being untested, and the likelihood of being malaria negative conditional on being tested in each treatment arm. We use parameter estimates obtained from data collection activities for these probabilities. $Pr(negative|untested)$ is estimated in the control group using data

collected from the lab tech activity which tested a random subset of 230 patients who purchased antimalarials for a suspected illness at 28 control group sites but did not get tested prior between January-February 2022. $Pr(negative|tested)$ is obtained in the control group from aggregate reported test positivity rates from 2547 tests done in 10 control group sites that conducted testing between January-February 2022 and kept records. In the treatment groups, $Pr(negative|untested) = Pr(negative) - Pr(negative|tested)$. $Pr(negative)$ is the unselected (for testing) malaria negativity rate, and is obtained from the control group testing data $(1 - (Pr(positive|tested)|Pr(positive|untested)))$, and $Pr(negative|tested)$ is directly obtained from the administrative transaction data from patients who purchased incentivized tests.

Finally, we calculate the time cost to patients of obtaining care for their malaria symptoms in the pharmacy setting. This is relevant because patients may experience longer visit times if they elect to be tested for malaria, which may affect their decision. We obtain estimates of total time spent at pharmacy seeking care from the patient exit survey data (in minutes) for each intervention arm, and multiply that by an estimate of the local hourly wage to obtain a monetary measure of the time cost for care-seeking.

The inputs needed to calculate all cost parameters can be found in Apppendix Table A1. For details on the sources of each parameter input for the costs, please see Appendix Tables A2 and A3. For details on formulas used to calculate the cost estimates, please see Appendix Table A4.

4.2 CEA Results

Below are details on calculating the benefits and costs that informed the final ICERs presented in the main text.

4.2.1 Benefits

In the control group, the probability of taking an ACT conditional on being malaria positive is $< 1\%$, in each intervention arm this probability is 3.5%, 4.3% and 3.3% in the patient subsidy group (T1), pharmacy incentives group (T2), and the combined group (T3), respectively. The total number of beneficiaries in each arm are 73, 253, 331, and 238 in the control group, T1, T2, and T3, respectively (assuming a hypothetical cohort of 10000 suspected malaria patients who sought care in each arm). These estimates can be found in the top panel of Table A5.

4.2.2 Costs

In the control group, the total implementation cost is $0, because there is no programmatic cost of administering any incentive interventions. The costs for the intervention arms are $2,574.00, $3,320.00 and $3,748.00 in T1, T2, and T3 respectively. These cost differences are due to the differential take up of incentivized rapid tests and ACTs in each intervention arm, with the combined arm having the largest share of patients purchasing incentivized rapid tests driving most of this difference. These cost estimates can be found in the bottom panel of Table A5.

For the societal perspective, we also include the direct medication costs of over-treating malaria negative patients in each of the intervention arms, and the time costs to patients for seeking malaria care at pharmacies in each of the intervention arms in addition to the program implementation costs. In the control group, the total social costs are $374,594, and the societal costs for the intervention arms are $364,226, $337,921, and $380,520 in T1, T2 and T3 respectively. The cost differences are due to differential take up of incentivized rapid tests and ACTs in each intervention arm, the arm-specific malaria test negativity rate, which is highest in the combined arm, and the share of malaria negative patients who purchase antimalarials unnecessarily. These cost estimates can be found in the bottom panel of Table A5.

Table A6 presents the incremental cost of each intervention relative to the next less expensive alternative. From the implementer perspective (Maisha Meds's perspective), the incremental costs are relatively small, since the incentive amounts are modest. The control group (status quo) is the cheapest alternative, and the combined arm is the most expensive. From a societal perspective, both patient subsidies and pharmacy incentives are cost-saving interventions relative to the control group because of the lower costs incurred from fewer malaria negative patients being treated unnecessarily and lower time costs of care-seeking due to lower patient volumes. The combined arm is the most expensive from a societal perspective, because of the larger time cost to patients seeking care, relative to the control group.

4.3 CEA Tables

Table A1: Cost Effectiveness Analysis Inputs

	Control (status quo)	T1 Patient subsidies	T2 Provider incentives	T3 Hybrid
	PARAMETER INPUTS			
P(tested)	0.081	0.348	0.275	0.282
P(untested)	0.919	0.652	0.725	0.718
P(malaria positive | tested)	0.021	0.1	0.16	0.12
P(malaria positive | untested)	0.106	0.027	-0.033	0.007
P(malaria positive)	0.127	0.127	0.127	0.127
P(ACT | malaria positive & tested)	0.001	0.996	0.956	0.962
P(ACT | malaria positive & untested)	0.086	0.02	-0.02	0
P(malaria negative)	0.873	0.873	0.873	0.873
Share of patients who purchased ACTs	0.867	0.722	0.7778	0.731
Incentive unit cost (RDT) ($)	$0.00	$0.90	$1.20	$1.10
Share of patients purchasing incentivized RDT	0	0.198	0.218	0.263
Incentive unit cost (ACT) ($)	$0.00	$1.10	$0.80	$0.90
Share of patients purchasing incentivized ACT	0	0.072	0.088	0.095
Average antimalarial treatment unit cost ($), untested	$1.92	$2.12	$1.49	$1.99
Share of untested patients (P(untested))	0.919	0.652	0.725	0.718
P(malaria negative | untested)	0.76	0.451	0.592	0.549
Average antimalarial treatment unit cost ($), tested	$4.02	$0.79	$1.98	$1.26
Share of tested patients (P(tested))	0.081	0.348	0.275	0.282
P(malaria negative | tested)	0.113	0.422	0.281	0.324
Time cost of seeking care (minutes)	18.04	17.71	16.33	18.39
Hourly wage ($)	$2.00	$2.00	$2.00	$2.00
Number of patients who accessed care	10000	10000	10000	10000

Table A2: CEA Probability Inputs - sources

	SOURCES
P(tested)	Intervention group means from Table 4, column 2 for all 4 arms
P(untested)	1 - P(tested)
P(malaria positive | tested)	Control group: administrative data from pharmacies on positivity rates (8 sites), positivity rates from random testing activity multiplied by share tested (19 sites); Treatment groups: test positivity rates from administrative transaction data of patients accessing tests through interventions.
P(malaria positive | untested)	Control group: lab tech testing random subset of control group patients; Treatment groups: P(malaria positive) from control group (unselected positivity rate); P(positive | tested), obtained from administrative transaction data as described above, P(malaria positive | untested) = P(malaria positive) - P(malaria positive | tested)
P(malaria positive)	P(malaria positive | tested) + P(malaria positive | untested) obtained from lab tech activity in control group, applied to all groups (base malaria positivity rate)
P(ACT | malaria positive & tested)	Control group mean from Table 5 column 4 * P(malaria positive | tested); Treatment group means from administrative transaction data for patients accessing incentivized tests and treatments
P(ACT | malaria positive & untested)	Group means from Table 5 column 6 * P(malaria positive | untested), for all 4 arms
P(malaria negative | untested)	Calculated directly from P(malaria negative) - P(malaria negative | tested) for all groups
P(malaria negative | tested)	Control group: lab tech testing random subset of control group patients; Treatment groups: P(malaria negative) from control group (unselected negativity rate); P(negative | tested), obtained from administrative transaction data as described above, P(malaria negative | untested) = P(malaria negative) - P(malaria negative | tested)

Table A3: CEA Additional Inputs - sources

	SOURCES
Number of patients who purchased ACTs	Intervention group means from Table 5 column 2; multiplied by 10000 hypothetical cohort
Incentive unit cost (RDT) ($)	Table C1; transaction completion incentives in T2 & T3 are included
Number of patients purchasing incentivized RDTs	Share from Administrative data (positive_rdt); multiplied by 10000 hypothetical cohort
Incentive unit cost (ACT) ($)	Table C1
Number of patients purchasing incentivized ACTs	Share from Administrative data (act_purchased); multiplied by 10000 hypothetical cohort
Average antimalarial treatment unit cost ($), untested	Administrative data (cost_malaria_products if rest_rdt_sales==0)
Number of untested patients	Inervention group means from Table 4, column 2; multiplied by 10000 hypothetical cohort
Average antimalarial treatment unit cost ($), tested	Administrative data (cost_malaria_products if rest_rdt_sales==1)
Number of tested patients	Inervention group means from Table 4, column 2; multiplied by 10000 hypothetical cohort
Time cost of seeking care	Mean time (mins) spent with provider by treatment arm, from patient survey (s4_a7_prov_treat_min)
Hourly wage ($)	Kenya Continuous Household Survey Program 2020
Number of patients who accessed care	Fixed at 10000 hypothetical cohort across all arms

Table A4: CEA Benefits and Cost Estimates - formulas

	FORMULAS
P(ACT | malaria positive)	P(ACT | malaria positive) = P(ACT | malaria positive & tested)P(malaria positive | tested)P(tested) + P(ACT | malaria positive & untested)P(malaria positive | untested)P(untested)
Number of patients taking ACTs	Administrative data (act_sales)
Number of beneficiaries	P(ACT | malaria positive)*Number of beneficiaries
	FORMULAS
Total cost of incentives	(RDT incentive*number of patients getting RDT) +(ACT incentive*number of patients getting incentivized ACT)
Total cost of over-treating malaria negative patients	P(malaria negative | untested)*number of untested patients purchasing antimalarials*cost of antimalarial treatment for untested patients + P(malaria negative | tested)*number of tested patients purchasing antimalarials*cost of antimalarial treatment for tested patients
Total time cost to patients seeking care	Number of malaria patients*average time spent with provider*average hourly wage
Total costs - societal perspective	Total cost of incentives + Total cost of over-treating malaria negative patients + Total time cost to patients seeking care
Total costs - implementer perspective	Total cost of incentives

Table A5: Benefits and Costs Estimates

	Control (status quo)	Patient subsidies	Provider incentives	Hybrid
		BENEFITS		
P(ACT | malaria positive)	0.008	0.035	0.043	0.033
Number of patients taking ACTs	8670	7220	7778	7310
Number of beneficiaries	73	253	331	238
		COSTS		
Total cost of incentives	$0.00	$2,574.00	$3,320.00	$3,748.00
Cost of over-treating malaria negative patients	$13,753.75	$7,392.35	$7,941.13	$9,012.15
Total time cost to patients seeking care	$360,840.00	$354,260.00	$326,660.00	$367,760.00
Total costs - societal perspective	$374,593.75	$364,226.35	$337,921.13	$380,520.15
Total costs - implementer perspective	$0.00	$2,574.00	$3,320.00	$3,748.00

Table A6: Incremental Costs

	Implementer perspective	
	Costs	Inc. cost
Control (status quo)	$0.00	-
TI - Patient subsidies	$2,574.00	$2,574.00
T2 - Provider incentives	$3,320.00	$746.00
T3 - Hybrid	$3,748.00	$428.00
	Societal perspective	
	Costs	Inc. cost
T2 - Provider incentives	$337,921.13	-
T1 - Patient subsidies	$364,226.35	$26,305.22
Control (status quo)	$374,593.75	$10,367.40
T3 - Hybrid	$380,520.15	$5,926.40

Implementer perspective includes only incentive costs. Societal perspective includes incentive costs, costs of overtreating malaria negative patients, and time costs. Incremental cost = incremental cost relative to next most expensive alternative.

Appendix B. Simulated control group detail

Table 6 presents results on treatment purchase conditional on patients having tested positive or negative fo malaria. In the intervention arms (T1, T2, T3), test positivity is observed directly from transaction records for patients that tested for malaria using the incentivized rapid tests. In these arms, we restrict our sample to this subset of patients. In the control group, we do not observe test positivity for individual patients. In the transaction data, we do observe whether clients purchased a rapid test and what their treatment choice was. From administrative aggregate testing records provided by a subset of control group sites that keep records on malaria positivity rates, we know that 24% of tests came back positive between January - February 2022. We use this test positivity rate, combined with the test positivity rate obtained from an independent random testing exercise of a subset of patients seeking care in control group sites, to simulate a control group subset that received a positive diagnosis and one that received a negative diagnosis, and use each of these simulated control groups as the comparison sample with the respective malaria-positive (malaria-negative) sample in the intervention arms.

Appendix C. Supplementary Tables and Figures

4.4 Appendix Tables and Figures

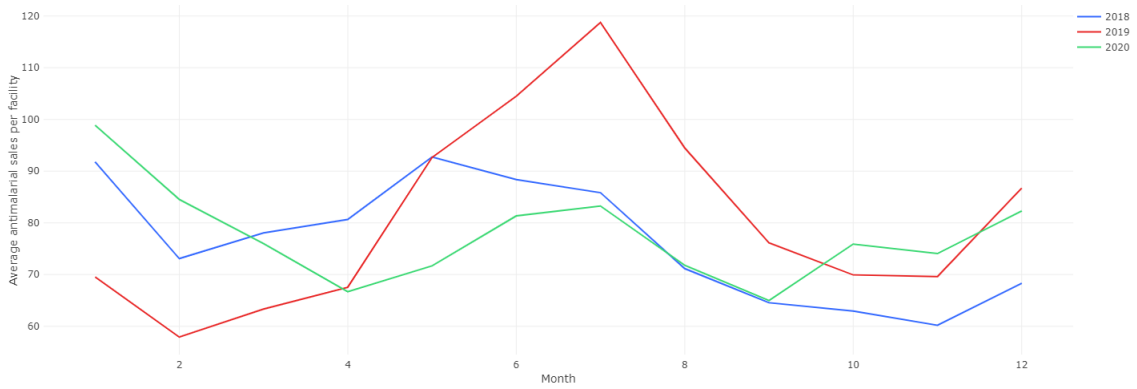

Figure C1: Malaria sales, seasonal trends (Back: 3.1)

Table C1: Incentive amount details, by treatment arm (Back: 2.2)

Subsidy and incentive amounts

	Control (C)	**Patient discount (T1)**	**Pharmacy incentive (T2)**	**Both (T3)**
Patient discounts? (USD)				
Rapid test	-	$0.90	-	$0.60
ACT (malaria +)	-	$1.10	-	$0.80
ACT (malaria -)	-	$0.00	-	$0.00
Provider incentives (USD)				
Rapid test	-	-	$0.90	$0.20
ACT (malaria +)	-	-	$0.80	$0.10
ACT (malaria -)	-	-	$0.00	$0.00
Transaction completion	-	-	$0.30	$0.30
Total incentive amount (USD)	$0.00	$2.00	$2.00	$2.00

Table C2: Baseline balance between facilities in sample and refusals (Back: 2.6)

Variable	(1) In sample	(2) Declined	(3) (2)-(1)
Number of months active on digital sales management tool	12.04	16.81	4.76**
	(9.43)	(8.52)	(0.01)
Average monthly malaria sales, 2019-2020	63.39	66.47	3.08
	(63.56)	(75.45)	(0.83)
Average monthly quality treatment sales, 2019-2020	54.41	61.25	6.84
	(54.26)	(72.61)	(0.59)
Average monthly rapid test sales, 2019-2020	6.48	5.39	-1.08
	(9.93)	(11.26)	(0.62)
Site was in earlier pilot study phase	0.16	0.23	0.07
	(0.37)	(0.43)	(0.32)
Site is in an urban area	0.31	0.34	0.04
	(0.46)	(0.48)	(0.69)
Site is in a malaria endemic county	0.84	0.86	0.01
	(0.37)	(0.36)	(0.84)
Site is a pharmacy	0.56	0.56	-0.00
	(0.50)	(0.51)	(1.00)
Observations	140	35	175

In sample facilities include those that were randomized to one of the study arms and were on-boarded successfully.

Table C3: Primary outcomes regressed on baseline characteristics (Back: 2.6)

	(1) Rapid test uptake	(2) ACT uptake with test	(3) ACT uptake without test
Months on sales management tool	.00143	.00197^{+}	-.00104
	(0.002)	(0.001)	(0.002)
Below median baseline malaria sales	.194**	.0369	-.155*
	(0.066)	(0.034)	(0.064)
Average monthly malaria sales, 2019-2020	-.000374	-.000687	-.00552*
	(0.001)	(0.000)	(0.002)
Average monthly ACT sales, 2019-2020	-.00211^{+}	-.000573	.00812**
	(0.001)	(0.001)	(0.003)
Average monthly rapid test sales, 2019-2020	.0157**	.0095**	-.0119**
	(0.003)	(0.002)	(0.003)
Site was in earlier pilot study phase	-.00984	-.00811	.0372
	(0.052)	(0.036)	(0.055)
Site is in an urban area	.0183	.0105	.0195
	(0.054)	(0.026)	(0.054)
Site is in a malaria endemic county	.0729	.0648**	-.105
	(0.073)	(0.024)	(0.073)
Site does not have clinical capabilities	.673**	.224**	-.652**
	(0.050)	(0.071)	(0.046)
% of staff who are female	.147^{+}	.0561	-.154*
	(0.078)	(0.039)	(0.075)
Age of pharmacy owner	.00767**	.00261*	-.00754*
	(0.003)	(0.001)	(0.003)
Average age of pharmacy staff	.000397	.000689	-.00217
	(0.006)	(0.002)	(0.005)
Female owner	-.202**	-.0851*	.182**
	(0.063)	(0.033)	(0.063)
Number of staff	.053	.0383	-.0728
	(0.060)	(0.029)	(0.059)
N	51486	51486	51486

Linear probability models for primary outcomes on baseline characteristics
Standard errors are clustered at the facility level
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table C4: Secondary outcomes regressed on baseline characteristics (Back: 2.6)

	(1) Antimalarial uptake overall	(2) ACT uptake overall	(3) ACT uptake w/ test, ACT sales
Months active on sales management tool	.000965	.000923	.00249
	(0.002)	(0.002)	(0.002)
Below median baseline malaria sales	-.00931	-.118*	.112*
	(0.029)	(0.051)	(0.053)
Average monthly malaria sales, 2019-2020	-.00297**	-.00621**	.0000527
	(0.001)	(0.002)	(0.001)
Average monthly ACT sales, 2019-2020	.00373**	.00754**	-.00211+
	(0.001)	(0.002)	(0.001)
Average monthly rapid test sales, 2019-2020	.00364*	-.00239	.014**
	(0.002)	(0.002)	(0.003)
Site was in earlier pilot study phase	-.0218	.0291	.000996
	(0.039)	(0.045)	(0.050)
Site is in an urban area	-.0373+	.03	.0146
	(0.022)	(0.040)	(0.043)
Site is in a malaria endemic county	.114**	-.0399	.111*
	(0.025)	(0.064)	(0.049)
Site is does not have clinical capabilities	.177*	-.428**	.738**
	(0.080)	(0.088)	(0.044)
% of staff who are female	-.0224	-.0976+	.115+
	(0.025)	(0.050)	(0.061)
Age of pharmacy owner	.00336**	-.00493+	.00765*
	(0.001)	(0.003)	(0.003)
Average age of pharmacy staff	-.00212	-.00148	-.000143
	(0.002)	(0.004)	(0.004)
Female owner	.0884*	.0974*	-.164**
	(0.034)	(0.042)	(0.054)
Number of staff	.038+	-.0345	.038
	(0.022)	(0.041)	(0.047)
N	265610	51486	40261

Linear probability models for secondary outcomes on baseline characteristics
Standard errors are clustered at the facility level
$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$

Table C5: Impact on antimalarial uptake, adjusted logistic regression models (Back: 3.1)

	Antimalarial sales overall		Non-ACT sales overall	
	(1)	(2)	(3)	(4)
Pooled treatment	.000427		-.000289	
	(0.023)		(0.003)	
Patient discount		.0259		-.00157
(γ_{T1})		(0.025)		(0.005)
Pharmacy incentive		-.00873		-.00444
(γ_{T2})		(0.032)		(0.004)
Patient discount and		-.00655		.00308
pharmacy incentive (γ_{T3})		(0.027)		(0.005)
Control mean	0.197	0.197	0.022	0.022
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2} \neq \gamma_{T3}$)		0.231		0.426
Wald test p-val ($\gamma_{T1} \neq \gamma_{T2}$)		0.156		0.544
Wald test p-val ($\gamma_{T1} \neq \gamma_{T3}$)		0.202		0.471
Wald test p-val ($\gamma_{T2} \neq \gamma_{T3}$)		0.943		0.200
N	265610	265610	258765	258765

Standard errors are clustered at the facility level

Controls: months active on platform, baseline malaria sales, female owner, strata and calendar month FE

Wald test comparisons of difference in marginal effects (γ) between treatment arms

Denominator is all patients that purchased malaria product during study period

Outcome 3: 45 obs dropped b/c multicollinearity (strata 11)

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$