Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial*

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Abstract

Both under- and over-treatment of communicable diseases are public bads. But absent enforceable regulation, efforts aimed at decreasing one run the risk of increasing the other. We study what this trade-off implies for the pricing of antimalarials. Since under-treatment can be deadly, the global health community is considering making the most effective class of malaria medications, called ACTs, available over-the-counter at heavily subsidized rates throughout Africa. However, ACT over-treatment will not just waste public resources, it will also contribute to drug resistance. Using experimental data from Kenya, we show that while the proposed subsidy substantially increases access, over-treatment is extremely common: just 56 percent of subsidized ACTs go to malaria-positive individuals. In this context, we show that price is a useful tool for targeting – a somewhat higher (but still heavily subsidized) ACT price increases the share of ACT-takers who are malaria-positive by 18 percentage points. Another potential tool for targeting is increased access to rapid diagnostic malaria tests. We show that demand for such tests is extremely high when tests are available over-the-counter and affordable, but compliance with test results would need to increase for a test subsidy to substantially improve targeting of subsidized ACTs.

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1 Introduction

Limiting the spread of infectious diseases has positive social benefits. As such, subsidies for prevention and treatment products are often central to infectious disease programs. Financing such subsidies is obviously subject to a budget constraint, however, and it is important to ensure that subsidy dollars are spent where they have the highest return. For products that have heterogeneous returns, the introduction of a subsidy creates a tradeoff between access and targeting. That is, subsidies for the product are likely to increase demand among both appropriate users, for whom the returns are indeed high, and among inappropriate users, for whom the benefits are marginal. This is the "menu-setting problem" described by Olmstead and Zeckhauser (1999).

This tradeoff between affordability and over-consumption is magnified for products for which overuse has negative social spillovers. For example, the (ineffective but quite common) use of antibiotics to treat viral infections contributes to antibiotic resistance. Likewise, antimalarial treatment in the absence of malaria contributes to antimalarial resistance. When people are uncertain about the cause of their ailment and the costs of under-treating can be deadly (e.g., untreated malaria is a major cause of child mortality in Africa), presumptive treatment is likely to be privately optimal if side effects are minimal and the treatment is subsidized and thus affordable. This makes the menu-setting problem even more pressing: the trade-off is not just between affordability and cost-ineffective consumption at a single point in time, but also between affordability today and effectiveness in the future.

This paper studies this menu-setting problem for the latest class of antimalarials, artemisinin combination therapies (ACTs). Artemisinin-based therapies now constitute the only effective class of antimalarials in Africa, where the malaria parasite has developed resistance to earlier generations of antimalarials, rendering them largely ineffective.[1] Due to continuing parasite resistance concerns, the use of artemisinin derivatives by themselves as monotherapies is highly discouraged by the World Health Organization (WHO) for the treatment of uncomplicated malaria. Instead, the WHO encourages the use of ACTs, which combine an artemisinin derivative with a partner drug, and thereby help protect the artemisinin derivatives from resistance.[2] However, the unsubsidized price of ACTs ($6-8) is prohibitive for

[1] Chloroquine (CQ) was introduced in Kenya in the late 1930s. P. falciparum resistance to chloroquine was first detected in 1978 and by the early 1990s, CQ resistance in the western part of the country was already 70 percent (Shretta et al. 2008). Subsequent innovations in antimalarial medicines have been successively less able to withstand parasite resistance. For example, resistance to Sulfadoxine-pyrimethamine (SP) emerged within five years of its introduction as first-line treatment for uncomplicated falciparum malaria in young children in Western Kenya (Terlouw et al. 2003).

[2] Combination therapies slow resistance because in order for a resistant parasite to arise, it must develop mutations that make it resistant to all drugs in the combination. When the combined drugs have differing modes of action, the probability of this event occurring is substantially lower than the probability of resistance

the great majority of households living in malarious regions, and as a result, in 2008, six years after ACTs were placed on the WHO's essential drugs list, fewer than 15 percent of African children with malaria were treated with ACTs (World Health Organization 2009). In response, a call was made for an ACT subsidy to achieve two main goals: (1) immediately *save lives,* by increasing access to ACTs and incentivizing their use over older, less effective drugs, and (2) *buy time*, by crowding-out monotherapies and thereby delaying resistance (Arrow et al. 2004). The Affordable Medicines Facility for malaria (AMFm) initiative, financed by major international aid agencies, was subsequently established to roll out a 95 percent subsidy to first line buyers of ACTs throughout Africa. At the time of writing, the subsidy was being piloted in 7 countries.

A primary objective of the AMFm subsidy is to reduce the price and increase the availability of ACTs in retail sector establishments, as many people seeking malaria treatment do so in loosely regulated, informal drug shops. A key issue is that these shops do not offer formal diagnosis. In this context, it is likely that a substantial decrease in ACT prices would be associated with increases in not only appropriate but also inappropriate ACT use. A high rate of over-treatment with ACTs is problematic for several reasons. First, if the ACT subsidy draws malaria-negative people from health clinics to the drug shop (reducing the chances they receive diagnostic confirmation), it could delay or preclude proper treatment of the true cause of illness and therefore increase morbidity and mortality, e.g. due to bacterial infections like pneumonia (Reyburn et al. 2004). Second, over-treatment with ACTs could affect inference about ACTs' effectiveness among the general population (Adhvaryu 2011). Third, a high rate of over-treatment for malaria may contribute to the selection of drug resistant parasites (Perkins and Bell 2008; White 2004). Finally, it is a waste of scarce subsidy money: the first two years of drug co-payments for the 7 pilot countries have already cost the AMFm around $250 million.

One way to preserve ACT access while minimizing over-treatment is to subsidize malaria diagnostic tests along with ACTs over-the-counter in drug shops. However, the effectiveness of this policy will depend on individuals' demand for and adherence to test results. Another potentially complimentary approach is to subsidize ACTs, but at a lower rate: while recent research has shown that cost sharing does not improve the targeting of *preventative* health products (Cohen and Dupas 2010; Ashraf et al. 2010), the impact of cost sharing on targeting of *curative* products like ACTs, which have much more immediate and salient benefits, may be quite different. We conducted a randomized controlled trial with over 2,700 households in rural Kenya to: (1) study the tradeoffs between ACT affordability and over-use in the context of the AMFm subsidy and (2) test an alternative to the AMFm subsidy regime

developing to any single drug alone (World Health Organization 2010a).

providing access to subsidized rapid diagnostic tests for malaria (RDTs) in tandem with subsidized ACTs.[3]

We show that subsidies for ACTs and RDTs substantially broaden access to these technologies, and that jointly subsidizing RDTs along with ACTs has the potential to improve the targeting of subsidized ACTs to people with confirmed malaria. Financing the RDT subsidy by reducing the ACT subsidy somewhat may be especially attractive, as modest decreases in the ACT subsidy improve the targeting of ACTs without meaningfully reducing ACT access. This is primarily due to two stark results from our experiment:

1. When ACTs are heavily subsidized, only 39 percent of individuals aged 14 and older who seek treatment for malaria at the drug shop actually have malaria (see Figure 1, solid black line).

2. The demand for ACTs is rather inelastic at low prices, even among the poorest households. Specifically, we see a modest 13 percent decline in the share of households buying ACTs at the drug shop when the retail price subsidy declines from 92 to 80 percent, corresponding to a 150 percent price increase (see Figure 2). What's more, such a reduction in the ACT subsidy does not meaningfully reduce access among those most likely to have malaria; rather, it screens out those less likely to have malaria.

In order for an RDT subsidy to be cost-effective (relative to an ACT subsidy alone), it is critical for people to be both willing to take the test and compliant with the test result. We find that willingness to test is very high: when offered a voucher for subsidized RDTs, more than 80 percent of households who visited the drug shop chose to take an RDT prior to making their ACT purchase decision. More generally, making subsidized RDTs available over-the-counter more than doubles the rate at which illnesses are tested for malaria. This is despite the fact that only 15 percent of households had heard of RDTs prior to our experiment. Compliance with the test result is not as high, however. In our context, about 49 percent of patients over the age of 5 who tested negative went on to purchase an ACT.[4] This behavior may in part reflect the fact that the status quo testing technology (a microscopic test offered at health centers) has a relatively high rate of false negatives and health practitioners themselves often ignore test results and prescribe antimalarials to those who test negative

[3]RDTs for malaria work similarly to rapid tests for HIV and do not require specialized equipment, such as a microscope or electricity. A small sample of blood is collected through a finger prick and placed on a testing cassette. The blood sample is exposed to a buffer solution, and the presence of malaria antigens can be determined within approximately 15 minutes. Non-clinical staff can easily learn to perform the test and interpret the results.

[4]At the time of this study, WHO and Kenya Ministry of Health guidelines recommended presumptive treatment (rather than diagnosis-based treatment) with an ACT for febrile children under the age of 5.

(Zurovac et al. 2006; Juma and Zurovac 2011). While RDTs have a lower rate of false negatives than microscopy in our study context, it might take some time for households to learn this.[5] Furthermore, individuals may still value taking the test even though they don't adhere to the results, either because the test result provides an indicator as to whether additional medication should be taken, or because the result helps individuals learn about the efficacy of ACTs and RDTs.

Overall, our estimates suggest that moving from the proposed AMFm policy regime to one that lowers the ACT subsidy and includes subsidies for RDTs could dramatically increase access to malaria testing and significantly improve the targeting of the ACT subsidy. In the experiment, moving from a 92 percent ACT subsidy to an 80 percent ACT subsidy along with subsidized RDTs increased the share of ACT-takers who are malaria positive at the drug shop by 24 percentage points. The majority (18 percentage points) of this impact comes from selection induced by the higher ACT price. However, the total impact could be substantially increased if full adherence to RDT results were achieved.

It is important to point out that this ACT+RDT subsidy regime is a second-best strategy. The first-best would be to make the ACT subsidy conditional on having a positive malaria test result. This first-best is unlikely to be enforceable at a reasonable cost, however. Overuse of prescription-only drugs is common even in highly regulated health care markets such as the US and Europe, due to physician agency problems (McGuire 2000). Similar agency issues are likely to be widespread in developing countries where monitoring of both private and public health care sectors is extremely limited (World Bank 2004).

While our results suggest that a slightly lower ACT subsidy (versus the AMFm proposal) would improve targeting without compromising access, our results make it very clear that a large ACT subsidy is needed in order to increase access, especially among the poor. We proxy socio-economic status by whether a household's female head is illiterate (about 38 percent of our sample) and find a substantial access gap in the absence of a subsidy: literate-headed households are over three times more likely to treat an illness episode with an ACT. A retail-sector ACT subsidy of 80 percent or more nearly closes this gap by disproportionately increasing access among illiterate headed households.

Beyond its immediate relevance to the AMFm, which will affect millions of households in rural Africa in both the short-run (affordability) and long-run (drug resistance), our paper contributes to the literature in three main ways. First, we contribute to the literature

[5]In populations with high parasite density, properly manufactured RDTs have a rate of false negatives generally under 5 percent in lab settings (World Health Organization 2010b) and around 8 percent in the field (de Oliveira et al. 2009). In contrast, the quality of microscopic testing varies greatly across lab technicians and with the quality of the equipment, and the rate of false negatives in the field was estimated at 31 percent by a 2002 study in Kenya (Zurovac et al. 2006).

on under-diagnosis and over-treatment, two major contributors to health care costs and a source of concern throughout the world (Das et al. 2008; Welch et al. 2011; Adhvaryu 2011). Second, we contribute to the literature on treatment-seeking behavior in resource-constrained environments, along with the earlier contributions on the impact of user charges for health care (see Griffin (1987) and Gertler and Hammer (1997) for reviews), and, more recently, the detailed studies by Leonard et al. (2002) in Tanzania, Banerjee et al. (2004) in Rajasthan (India), and Leonard (2007, 2009) in Tanzania and Cameroon, respectively. Third, our paper adds to a fast-growing experimental literature on user fees for health products whose appropriate use generates positive externalities. So far this literature has focused on optimal pricing for preventative health products, such as bednets or water purification kits, for which over-use is not a problem, and for which the objective of the social planner is to expand access while limiting *under-use* among subsidy beneficiaries.[6] In contrast, this paper considers the price-setting problem that arises when over-use generates negative externalities (in our case, through drug resistance). While earlier evidence from the same region of Kenya showed that cost-sharing did not improve targeting of malaria prevention subsidies (Cohen and Dupas 2010; Dupas 2012), here we find evidence that higher rates of cost-sharing can improve targeting of malaria treatment subsidies. This targeting effect is facilitated by the dosing structure of ACTs. A higher price-per-pill increases the price substantially more in absolute terms for adults (who require a higher dosage) than for children. Such a proportional price increase results in a greater decrease in demand among adults, for whom the expected returns from ACT treatment are lower. Not all of the targeting benefits are driven by this pricing structure, however, as adult ACT-takers are more likely to be malaria-positive at higher ACT prices, suggesting some level of private information about underlying malaria risk.

The remainder of the paper proceeds as follows: Section 2 provides some background facts on the malaria burden and treatment options in rural Africa, as well as the proposed AMFm subsidy. Section 3 develops a model of treatment-seeking behavior in this environment, and identifies the key tradeoffs inherent to heavily subsidizing ACTs. Section 4 describes our experimental design and data. We present results on the impact of an AMFm-type subsidy in Section 5. We then discuss the impacts of alternative subsidy regimes in Section 6.

[6]See Cohen and Dupas (2010), Dupas (2012), Hoffmann (2009), and Tarozzi et al. (2011) on bednets; Ashraf, Berry, and Shapiro (2010) and Kremer et al. (2011) on water purification; and Dupas (2011) for a review.

2 Background

Malaria is estimated to cause 200 million illnesses and to kill close to one million people every year – the great majority of them in Africa, and the great majority of them among children under age five (World Health Organization 2009). Children under 5 are most vulnerable to acquiring and dying from malaria because immunity to malaria develops with repeated exposure. How readily these children can access effective antimalarials when they get infected is thus a very important determinant of overall malaria morbidity and mortality. Unfortunately, due in large part to the high cost of ACTs, the vast majority of children under the age of 5 are treated not with ACTs, but with older antimalarials to which the parasite has gained resistance (World Health Organization 2009).

To address this cost issue, many African countries (including Kenya) have a policy of providing ACTs for free in public health facilities. In practice, treating malaria at public facilities has a number of drawbacks. First, public health clinics are known to have high rates of provider absenteeism, limited opening hours, and stock outs of essential medicines, including ACTs (Kangwana et al. 2009; Chaudhury et al. 2006). Although public health facilities sometimes offer blood slide microscopy tests for malaria, the accuracy of microscopic diagnosis in rural settings is quite variable (see footnote 5 above). Consequently a substantial share of individuals are prescribed antimalarials even if they test negative (Zurovac et al. 2006; Juma and Zurovac 2011). Finally, even though ACTs are free in public facilities, the direct and indirect costs of seeking treatment for malaria in the public sector can be high if fees are charged for consultation and/or diagnosis (as is often the case in our study area) and if it is costly or time consuming to travel to the facility and be seen by a medical professional.

Given the drawbacks of rural health facilities, it is common for households to treat illnesses with over-the-counter medication purchased at drug shops. For example, the retail sector accounted for 40-97 percent of all antimalarial sales in the 7 AMFm pilot countries *before* the AMFm subsidy began (Arnold et al. 2012). Our own study population reflects this broad pattern, with 52 percent of antimalarials procured from a drug shop at baseline (Appendix Table A1).

The two main benefits to treating an illness at a drug shop, rather than a public health facility, are convenience and choice. Most households live a short walk away from such a shop, and these shops are open reliably and offer a wide variety of medications. The education levels and credentials of drug shop owners vary widely, but they are often asked by patients for treatment recommendations (Patouillard et al. 2010; Marsh et al. 2004). Drawbacks of drug shops include the lack of skilled medical staff and diagnostic capability, the risk of receiving lower quality or counterfeit drugs (Bjorkman et al. 2012), and the absence of

emergency medicines and equipment to treat severe malaria infections.

Given drug shops' large share of the antimalarials market, the AMFm explicitly seeks to reduce the price and increase the availability of ACTs in the retail sector. Through a factory-gate co-payment (a "global subsidy"), the program aims to reduce the price of ACTs by roughly 95 percent to first line buyers, such as governments, NGOs and wholesalers (Global Fund to Fight AIDS, TB and Malaria 2010). The final price to consumers in the private sector is not formally restricted, but the aim is for ACTs to be cheap enough for most rural, poor populations to afford them and to crowd-out other antimalarials. For example, the Kenyan government set a "recommended retail price" for ACTs purchased under the AMFm of 40 Kenyan Shillings (KSh), which is about \$0.50, similar to Uganda (\$0.47) but lower then the recommended retail price for ACTs in other AMFm pilot countries such as Niger (\$0.69), Tanzania (\$0.62) and Ghana (\$0.93).[7] The AMFm launched in early 2011 as a pilot in 7 countries (including Kenya). Our study was conceived and implemented in 2008/2009, when the AMFm was under consideration but had not yet started its pilot.

3 A Model of Malaria Treatment Seeking Under Uncertainty

This section develops a model of malaria treatment seeking behavior in the environment described above. The goal of the model is to provide a framework for our empirical analysis while highlighting the access/over-treatment tradeoff inherent to the AMFm approach of subsidizing retail sector ACTs. The tradeoff is embedded in the following two policy parameters of interest: (1) the share of true malaria episodes that do not get treated with ACTs; we denote this as "UT" for "under-treatment"; and (2) the share of non-malaria episodes that are treated with ACTs; we denote this as "OT" for "over-treatment".

The objective of the social planner is to decrease UT while limiting the increase in OT. In other words, the goal is to reduce the number of type II errors (false negatives) without increasing the number of type I errors (false positives) too much. Formally, the problem of the social planner is thus to maximize a malaria-treatment objective function (some $f(UT, OT)$, with $f_{UT} < 0$ and $f_{OT} < 0$), subject to a budget constraint. To stay as general as possible, we avoid imposing a specific functional form for the social planner's objective function.

[7] A price of KSh 40 corresponds to a 92 percent reduction in ACT retail prices in our study area (i.e. the implicit expectation is that the 95 percent AMFm subsidy at the top of the supply chain moves down the chain more or less proportionally). Evidence on ACT prices in the retail sector observed after the pilot AMFm subsidy was introduced in Kenya in 2011 suggests the retail price indeed fell to a level close to KSh 40 on average.

In our emprical analysis, we identify the impact of the different subsidy regimes on UT and OT by focusing on two related parameters: access, A (the share of illness episodes treated with ACTs) and targeting, T (the share of ACT-takers who are malaria positive). Specifically, we can map access and targeting to UT and OT as long as we know the share of all illness episodes that are truly malaria.[8] In what follows, we present a theoretical framework to discuss how ACT and RDT subsidies will affect these key parameters.

3.1 Model Setup

We consider an environment where, when faced with an illness shock, the household has three possible actions, $a \in \{s, h, n\}$: (1) buy ACTs at the drug shop: $a = s$; (2) seek diagnosis at a formal health facility and receive ACTs if positive: $a = h$; (3) purchase other non-ACT drugs at the drug shop (e.g. antipyretics) or do nothing: $a = n$. When a household gets an illness shock, the household observes the symptoms of the illness and subjectively assesses the probability π that the illness is actually malaria. We assume that households' subjective malaria assessments are accurate, in that a household's self-assessed probability of having malaria is equal to the true probability conditional on characteristics of the illness.[9] The expected value of taking a particular action $a \in \{s, h, n\}$ depends on this probability, and is denoted by $V^a(\pi)$. It can be decomposed as follows:

$$\begin{aligned} V^a(\pi) &= \pi\left[U_P^a(\pi) - p_P^a(\pi)\right] + (1-\pi)\left[U_N^a(\pi) - p_N^a(\pi)\right] \\ &= \pi V_P^a(\pi) + (1-\pi) V_N^a(\pi) \end{aligned}$$

where $U_M^a(\pi)$ is the utility obtained from taking action a when the individual's true malaria status is $M \in \{P, N\}$ (i.e., malaria positive or malaria negative) and p_M^a is the expected price paid for treatment when the individual's true malaria status is M.[10] Note that the utilities and prices may be a function of the malaria probability π. For example, if the severity of symptoms is increasing as π increases, then individuals may expect to pay more to treat the illness, particularly when it is not actually malaria.

We assume that the value of taking action $a = n$ (doing nothing/taking non-ACT medication at the drug shop) becomes relatively less attractive as π increases. That is, we assume

[8] Denote overall malaria prevalence as Π. Then $UT = 1 - TA/\Pi$ and $OT = A(1-T)/(1-\Pi)$.

[9] It is straightforward to loosen this assumption and allow for biased assessments. All the results below go through as long as actual malaria probability is strictly increasing in subjective malaria probability.

[10] We assume that $V^a : \pi \to \mathbb{R}$ is a function, not a correspondence. This simplifies our analysis and still provides useful guidance for the empirical work, but it is not a trivial restriction: the assumption would be violated if, for example, two illness episodes had equal malaria probability but different likelihoods of being other illnesses of differing severity, such as a cold or pneumonia.

that $V^a(\pi) - V^n(\pi)$ increases with π for $a \in \{s, h\}$. For convenience, we also assume that $V^a(\pi)$ is continuous in π for all for $a \in \{n, s, h\}$.

An individual will seek ACT treatment at the drug shop if

$$V^s(\pi) \geq max\left\{V^h(\pi), V^n(\pi)\right\} \tag{1}$$

In practice, for a given value of π there may be heterogeneity in these valuations in the population. For example, the cost (in utility terms) of higher priced ACT medication will be lower for wealthier households. In order to study heterogeneity and clarify the potential distributional impacts of a subsidy policy, we consider two types of households, "rich" and "poor". We assume that, absent the subsidy policy, rich households are able to afford unsubsidized ACTs and travel to the health center, whereas poor households cannot: they always either hope an illness resolves on its own or they purchase inexpensive medication at the drug shop. Figure 3, top panel, graphs the value curves for the rich (left panel) and the poor (right panel) in the absence of a subsidy. Without loss of generality, we have renormalized the value functions so that $V^n(\pi) = 0$ for all π. The figure presents the case where presumptively buying an ACT is preferred to traveling to the health center at higher malaria probabilities (i.e. when people are most certain an illness is malaria). This is one plausible scenario, but other configurations are certainly possible (and the results below do not depend on this specific case holding in the data). Under such a scenario, "rich" households with a malaria probability above π_2 elect to purchase an ACT from the drug shop. Those with a malaria probability between π_1 and π_2 elect to seek care at the health center, where they can consult with a health professional and/or be tested for malaria before choosing a treatment. Finally, those rich households with a malaria probability below π_1 choose to do nothing or to buy an antipyretic or other non-ACT medication from the drug shop. For "poor" households, neither ACTs at the drug shop nor health center visits are affordable, and as a result they choose to do nothing or to buy something else from the drug shop, regardless of their malaria probability.

3.2 Impact of an ACT Subsidy at the Drug Shop

We first consider the impact of a decrease in the price of ACTs at the drug shop in the absence of any diagnostic testing in the retail sector. A decrease in the price of ACTs in the retail sector (holding other prices constant) will decrease the cost of purchasing an ACT at the drug shop, whether one truly has malaria or not (i.e., both $p_P^s(\pi)$ and $p_N^s(\pi)$ decrease). This increases the left hand side of inequality (1) while leaving $V^h(\pi)$ and $V^n(\pi)$ unchanged for all values of π. Given this, purchases of ACTs at the drug shop will increase. Access (the

fraction of illnesses treated with ACTs) therefore increases, even if all crowd-out is from the health center: in this case malaria negative illnesses previously screened out at the health center will now receive ACTs. Note that this increase in access always comes at the price of decreased targeting. This is because crowd-out from the health center always worsens targeting, and crowd-out from doing nothing (action n) increases ACT taking for illnesses with lower malaria probabilities than those that were treated before the price reduction.

When there is heterogeneity in valuations in the population, however, an ACT subsidy need not worsen targeting. To fix ideas, Figure 3, bottom panel, illustrates the impact of the subsidy policy on behavior of the rich and the poor separately. For the rich, reducing the price of ACTs at the drug shop will lead to crowd-out from the health center among illnesses with intermediate malaria probabilities, and, if the ACT subsidy is large enough, crowd-out from other options among those with a low malaria probability. For the poor, illnesses with the highest malaria probabilities are now treated with an ACT. If the subsidy policy crowds in enough high-malaria-probability poor relative to low-malaria-probability rich, then overall targeting will improve.

This underscores that it is important to pay attention to distributional impacts of the ACT subsidy. In particular, the subsidy would be especially attractive if it increased take-up among high-positivity populations who didn't have access to ACTs before (this is certainly the intent of the AMFm). On the other hand, it is possible that the subsidy would mostly go to populations who would have gotten the ACT regardless of the subsidy policy (at a health center, for example), or to very low positivity populations.

3.3 Impact of Adding an RDT Subsidy at the Drug Shop

Now suppose that at some cost, an individual can receive a diagnosis (take an RDT) for malaria at the drug shop. There are two primary advantages of taking a test: (1) If the test is negative, the individual avoids the need to pay for an antimalarial. This is particularly attractive when the price of the RDT is less than the price of an antimalarial. (2) If the test is negative, the individual will be more likely to select an appropriate medication.[11] Note that RDT provision has both an intensive and an extensive margin effect. The intensive margin effect applies to individuals for whom purchasing an ACT at the drug shop is optimal in the absence of an RDT subsidy. These individuals will continue to seek care from the drug shop and will choose to use an RDT if the expected gain in utility and/or savings on excess medicine exceeds the cost of the RDT. As long as some of these individuals comply with the test result, this will reduce over-treatment while leaving under-treatment unchanged.

[11]There are other advantages to taking an RDT that we discuss in section 6.3.

Targeting therefore improves while access declines.

On the extensive margin, the RDT subsidy may draw a set of illnesses to the drug shop that would have otherwise sought treatment elsewhere. As long as all these individuals comply with the test result, under-treatment will decrease (weakly, if all crowd-out is from the health center) while over-treatment will not change – this works to increase both targeting and access. Then *in the perfect compliance case* the intensive and extensive margin effects imply that targeting increases, but the impact on access is ambiguous. However, if not all individuals crowded into the drug shop comply with the RDT test result, the extensive margin effect on targeting becomes ambiguous, since non-compliance increases over-treatment.

Overall, this simple model illustrates two key insights. First, while using an ACT subsidy to decrease under-treatment comes at the expense of increasing over-treatment, the relative magnitude of the two effects is ambiguous. The net effect on targeting depends on the shapes of the value curves $V^a(\pi)$ for $a \in \{s, h, n\}$, heterogeneity in valuations, and baseline treatment seeking behavior (e.g. the relative prevalence of the "rich" and the "poor"). Second, RDTs could potentially allow for increased access without increasing over-treatment – this, however, will depend on takeup and patients' adherence to the test result. In what follows, we describe our field experiment, which we designed in order to estimate the key parameters UT, OT, A, and T under several different ACT-RDT subsidy regimes.

4 Study Design and Data

4.1 Experimental Design

The experiment was conducted in the districts of Busia, Mumias and Samia in Western Kenya between May and December of 2009. Malaria is endemic in this region with transmission occurring year-round, but with two peaks corresponding to heavy rain in May-July and October-November. Like much of sub-Saharan Africa: it is rural and poor, with the majority of household heads working as subsistence farmers.

We selected four drug shops, in four rural market centers and sampled all households in the catchment area (within a 4km radius) of each of these shops.[12] We then visited each household to administer a baseline survey to the female head of household (whenever possible), at the end of which two vouchers for ACTs and, when applicable, two vouchers for RDTs were distributed. Enumerators explained that ACTs are the most effective type of

[12]Participating drug shops were chosen on the basis of several criteria including distance from drug shops participating in other public health interventions, shop owner qualifications, length of time the shop had been in business and the number of daily customers.

antimalarial and, if the household received an RDT voucher, what the RDT was for and how it worked.[13] The vouchers stated the drug shop at which the products could be purchased and did not have expiration dates so as to avoid incentivizing households to redeem vouchers in the absence of an illness episode. Of the 2,928 households sampled during the census, 2,789 (95 percent) were reached and consented to the baseline survey (baseline survey non-completion is uncorrelated with treatment status).

The experimental design is illustrated in Figure 4. Households were randomly assigned to one of three core groups, corresponding to the three policy regimes of interest. The "No Subsidy" group received vouchers to purchase unsubsidized ACTs at the market price of KSh 500 (just under $6.25). This treatment arm is meant to capture the no-subsidy status quo in Kenya, where over-the-counter ACTs are expensive and RDTs are not available in drug shops.[14] The second group received the ACT subsidy only. This treatment is meant to reflect outcomes under the planned form of the AMFm in Kenya (i.e. without RDTs). Within the "ACT subsidy only" group, households were randomly assigned to a retail price subsidy level of 92, 88 or 80 percent (corresponding to $0.50, $0.75 and $1.25 for an adult dose, respectively). The 92 percent subsidy level corresponds to the Kenyan government's target retail price of KSh 40 under the AMFm. The lower subsidy amounts reflect prices that could be realized if the subsidy amount were reduced, potentially to fund RDTs.[15] Since ACTs are priced by dose, with the appropriate dose determined by age, the four ACT subsidy levels (0, 80, 88 and 92 percent) differed in the price-per-pill to which a household was entitled. Figure A1 in the Appendix illustrates the pricing and dosing regimens in the study. The third group received vouchers for both subsidized ACTs and RDTs, with households again randomized into one of three ACT subsidy levels. All ACTs and RDTs were provided by trained study officers posted at the drug shop.

The study incorporated two additional layers of randomization. First, a sub-sample of households was also randomly selected for a "surprise RDT" offer at the drug shop. Specifically, if these households came to the drug shop to redeem their ACT voucher, but did not redeem an RDT voucher (either because they were not in the RDT treatment group or because they chose not to) they were asked, *after they had paid for the ACT*, whether they

[13]The ACT used in this study was Coartem (Artemether Lumefantrine), produced by Novartis Pharmaceuticals. The RDT was the ICT Malaria Pf test, produced by ICT Diagnostics. This type of test only detects the *P. falciparum* strain of malaria, which accounts for 98 percent of all malaria infections in Kenya and is by far the most deadly strain of malaria (Kenya Division of Malaria Control 2011).

[14]The rationale behind distributing a voucher for unsubsidized ACTs to the control group was to harmonize the level of "endorsement" of the local drug shop across groups, as well as harmonize the amount of information (on effectiveness and availability) provided about ACTs across groups.

[15]This price range also roughly corresponds to the price range for the cheapest to the most expensive non-ACT antimalarials available in drug shops in our area of study.

would be willing to take an RDT for free.[16] If the patient (the person for whom the ACT voucher was redeemed) had not come to the shop, one of the two study officers accompanied the client back home in order to perform the test on the patient. The purpose of this treatment was to obtain data on malaria positivity among ACT-takers in the absence of RDT selection effects. Second, households in the ACT+RDT subsidy group were assigned to one of three RDT subsidy levels: a free RDT, an RDT for \$0.20 (corresponding to an 85% subsidy) and an RDT for \$.20 that was refundable if the test was positive and an ACT was purchased. The purpose of this RDT price variation was to estimate the willingness to pay for RDTs. In practice, we find few substantive differences across the RDT-subsidy levels with respect to take-up and composition (see Appendix table A4), so we pool them together in our analysis for simplicity.

The randomization of households was done using a computerized random number assignment algorithm and was stratified by drug shop, by the household's distance to the drug shop (in quartiles) and by the presence of children in the household. At the end of the experiment we visited households again to administer an endline survey. At that time, households were informed that the study was ending, and unused vouchers were collected back from households.[17]

4.2 Baseline Characteristics of Study Sample

Table 1 presents baseline household characteristics and tests for balance across treatment groups. We interviewed the female household head roughly 90 percent of the time. Our respondents are typically married, with five years of education and four dependents, and 62 percent are literate. On average, households live 1.7 kilometers from the drug shop for which vouchers were given and 6.6 kilometers from the nearest public health facility. While roughly 40 percent of households had heard of ACTs at baseline, less than 15 percent had heard of RDTs. Columns 4-6 present p-values on F-tests for differences in baseline characteristics across treatment groups. There are no significant differences across treatment groups, other than for the number of acres owned and the age distribution in the household. In particular, our control group has slightly older household heads, with, as a consequence, a significantly higher fraction of adults. Since age is highly correlated with malaria positivity, a lack

[16] Respondents could get a refund for the ACT they had just purchased if the test result was negative. 93% of those offered the surprise RDT consented to be tested (or consented for their sick dependent to be tested).

[17] As compensation, all households were given a tin of cooking fat at endline regardless of whether or not they returned any vouchers to us. Because information that the vouchers were being recalled might have led to presumptive voucher redemption around the time of the endline survey, in the analysis below we ignore all redemptions that took place after the rollout of the endline survey.

of balance across treatment groups in the age composition of households could confound estimates of treatment assignment on uptake and targeting, even though the magnitude of the age differences is not large. Therefore, in all of the results that follow we control for the age of the household head.[18]

4.3 Data

We use three types of data in the analysis that follows. The first is what we liberally call "administrative" data based on voucher redemptions at the drug shop; the second is an endline survey administered to all households in the study; and the third dataset maps reported symptoms and patient characteristics to malaria test results for a universe of illness episodes experienced by our study population.

Administrative Data: Drug Shop Transactions The administrative data captures the details of drug shop transactions, including medicines bought, symptoms, patient characteristics, and true malaria status in case an RDT was administered. These data were recorded by trained enumerators posted at each of the four participating drug shops during opening hours, every single day throughout the study period. These data include information on over 1,700 drug shop visits made by study households over a four-month period.

Endline Survey The endline survey was administered about four months after the vouchers had been distributed. Only 5 percent of households surveyed at baseline were not reached at endline, and attrition was balanced across treatment arms. The endline survey asked households to recall all illness episodes that involved fever, chills, headache, sweats, nausea, cough, or diarrhea, that the household experienced in the four months that followed the baseline. For each of these episodes, we collected information about symptoms, where treatment was sought, what type of malaria test (if any) was taken and what medications were purchased. We find no systematic differences in illness reporting at endline across treatment groups (Appendix Table A2). In the analysis below, we focus only on the first illness episode reported by each household, since we want to limit ourselves to illness episodes for which households still had study vouchers. Ninety-five percent of households reported at least one illness episode over the study period.

[18] We also checked balance at a finer level of granularity by regressing the characteristics in Table 1 on a vector of dummies for each unique treatment combination and testing whether these dummies were jointly equal to 0. All p-values are greater than 0.1 for these specifications.

Symptoms Database In our data, we only observe actual malaria status for those illness episodes for which (1) care was sought at a participating drug shop and (2) an RDT was administered at the time of the drug shop visit. This allows us to construct very accurate estimates of targeting (T) for those seeking treatment at the drug shop. However, constructing an overall estimate of this parameter requires data on malaria positivity of *all* illness episodes. To address this, we construct a predicted malaria positivity index for all illness episodes, based on a "symptoms database" collected for our study population. We collected these data approximately one year after the study ended during unannounced home visits. At the visit, trained enumerators asked if anyone was feeling ill, and if yes, they collected information about symptoms (using the same instrument as that used in the endline survey) and then tested the patient for malaria with an RDT. We use these data on illness-specific characteristics to impute a malaria probability to the universe of illness episodes enumerated at endline and all illnesses observed at drug shops. The appendix gives additional detail on this process.

5 Results: Impacts of an AMFm-type ACT Subsidy

5.1 Malaria Treatment Seeking Behavior in the Absence of a Retail ACT Subsidy

As highlighted by the model, the impact of introducing an ACT subsidy will depend on how people choose to treat malaria (buying ACTs at the drug shop, going to the health center, or doing nothing/buying other medicines) across malaria risk levels. Figure 5 plots the frequency of these three possible actions by predicted malaria positivity among the control ("No Subsidy") group both overall (Panel A) and separately by SES (proxied by head literacy, Panels B and C). The figure graphs results of local linear regressions of the following form:

$$y_{eh} = g\left(predpos_{eh}\right) + \varepsilon_{eh} \tag{2}$$

where y_{eh} is the outcome of interest for illness episode e reported at endline by household h and $predpos_{eh}$ is our measure of predicted malaria positivity for that illness episode (given the reported symptoms). Solid gray vertical lines demarcate overall tertiles of predicted positivity, while the dashed gray vertical line demarcates the median.[19]

[19] We calculated quantiles using all first illness episodes for both treatment groups and the control group. We do not change these quantiles when conducting subgroup analysis. When graphing the local linear results, we omit the results for the observations with the upper- and lower-most 2.5 percent of predicted positivity to avoid illustrating imprecisely estimated tails.

The figure highlights a sharp contrast in treatment-seeking behavior by SES. For literate households, the likelihood of taking a non- or sub-therapeutic action is clearly decreasing with malaria positivity, in favor of health center visits and purchasing ACTs at the drug shop (Figure 5, Panel B). We can draw a number of conclusions from these patterns. First, they suggest that our predicted positivity measure captures important heterogeneity in treatment seeking behavior. Second, literate households' treatment decisions appear to depend on an illness's malaria likelihood, and treatment decisions appear consistent with the scenario for "the rich" described in the theory section and illustrated in Figure 3, left panel.

The patterns for illiterate households in Figure 5, Panel C are notably different. The share of illness episodes treated at the health center is very low overall, with the highest rate of health center usage at intermediate positivity rates. The share of episodes for which an ACT is bought at the drug shop is exceptionally low (likely due to the high retail price of ACTs) and increases only weakly with malaria positivity. This is consistent with the scenario for the "poor" discussed in the theory section and illustrated in the right panel of Figure 3.

These results suggest that an ACT subsidy regime could be especially beneficial for illiterate-headed households. In contrast, the subsidy has less scope to improve outcomes for literate headed households, who are much more likely to access ACTs for high-malaria-probability illness episodes.

5.2 What Happens When a Large ACT Subsidy is Introduced at Drug Shops?

We now analyze the impact of introducing a large ACT subsidy in the retail sector. To focus first on the subsidy versus no subsidy comparison, we pool the three ACT subsidy treatments (92 percent, 88 percent, and 80 percent) into a single group. (In subsection 6.1 we will examine the sensitivity of the impacts to the subsidy level). To unpack treatment seeking behavior we first look at the impact on provider choice (where to seek treatment) and then at treatment choice. We present the results both graphically (plotting local linear regressions in Figure 6) to illustrate broad patterns and in Tables 2 and 3 to provide magnitudes and standard errors.

We present two sets of specifications in the tables. We first consider overall mean effects, estimating the following equation:

$$y_{eh} = \delta + \alpha ACTsub_h + x_h'\gamma + \lambda_{strata} + \varepsilon_{eh} \tag{3}$$

where y_{eh} is the outcome of interest for illness episode e in household h. $ACTsub_h$ is a dummy variable equal to 1 if the household was randomly selected to receive an ACT subsidy, x_h is

a vector of household level controls,[20] and λ_{strata} are strata fixed effects.

We then examine impacts by tertile of predicted malaria positivity, running:

$$y_{eh} = \delta_0 + \sum_{j=1}^{3} (\alpha_j ACTsub_h \times tert_{jeh} + \delta_j tert_{jeh}) + x_h'\gamma + \lambda_{strata} + \varepsilon_{eh} \quad (4)$$

where $tert_{jeh}$ is a dummy variable equal to 1 if episode e in household h is in tertile j of overall predicted malaria positivity.[21]

The analysis focuses on the first reported illness episode experienced by the household to ensure that a voucher could be used for treatment if so desired. If more than one household member got sick simultaneously, we include all concurrent first episodes, and therefore cluster the standard errors in all illness episode regressions at the household level, as this is the unit of randomization. Results are similar, though slightly attenuated, if we also include second illness episodes following the baseline survey. Finally, note that households who did not receive an RDT voucher but were randomly selected for a surprise RDT test are excluded from this analysis, as the results of the surprise test could have impacted their ultimate medication choice.[22]

5.2.1 Impacts on Provider Choice

We first consider how the retail-sector ACT subsidy affected the likelihood that an illness was treated at the drug shop, at the health center, or not treated at all. The first three columns in Table 2 present results for all households and show that the ACT subsidy increased treatment seeking at the drug shop by 15.9 percentage points (32 percent), while decreasing treatment seeking at the health center by 7.6 percentage points (26 percent). Furthermore, the subsidy substantially increased care-seeking: the fraction of households not seeking any care decreased by 9 percentage points (42 percent). These effects are significant at conventional levels (though only marginally so for the health center). Columns 4-9

[20] We control for household head's age because the age composition of control households is tilted more towards adults, as illustrated by Table 1 and discussed above. We also control for whether the household was sampled for an RDT subsidy.

[21] Since the tertile dummies are generated regressors, we present bootstrapped standard errors (clustered at the household level) for all these specifications. We bootstrap by generating 500 replicant datasets where households are sampled with replacement from the core sample. For each replicant sample, we recalculate predicted malaria positivity and positivity tertiles.

[22] We do not exclude households sampled for a surprise test if they were also sampled to receive RDT vouchers. That is because 80 percent of them elected to redeem their RDT voucher anyway, conditional on visiting the drug shop (where they would otherwise have been surprise tested), and F-tests of the significance of surprise testing selection confirm that the surprise testing had no significant impact on behavior for this group. Our results are largely unchanged, though somewhat less precisely estimated given the drop in sample size, when excluding these households.

in Table 2 present the results broken down by SES (literate-headed vs. illiterate-headed). While the subsidy decreased rates of not seeking care for both literate- and illiterate-headed households (our estimates are just short of marginal significance for illiterates), only literate-headed households were crowded out of the health center.

The top panel of Figure 6 and the second panel of Table 2 present evidence on how these impacts vary with the underlying malaria probability of the illness episodes. Crowding into the drug shop occurs across all tertiles of predicted positivity, with crowding out from doing nothing concentrated in the lower tertile of predicted positivity and crowding out from the health center concentrated in the middle tertile of predicted positivity. Indeed, for the health center and doing nothing we reject that crowd-out patterns are the same across tertiles at the 90 percent level.

5.2.2 Impacts on Overall Access to ACTs

We now turn to the key outcome of interest – how the retail sector ACT subsidy affects access to ACTs, and how this varies with the likelihood that an illness is malaria. The results are presented in Table 3, and are extremely straightforward: overall, the subsidy increases the likelihood that an illness is treated with an ACT by nearly 60 percent (15.3 percentage points, significant at the 99 percent level), and this increase can be seen across the entire spectrum of predicted malaria positivity.

What is particularly striking is the breakdown by literacy status, which reveals desirable distributional properties of the subsidy: the increase in ACT access is primarily for illiterate-headed households. Overall, the retail sector ACT subsidy considerably decreases the access gap – while literate households in the control group are over three times more likely to take an ACT than illiterate households (36.5 percent for literate-headed and 10.8 percent for illiterate-headed households), the introduction of an ACT subsidy at the drug shop boosts coverage rates to 44.6 percent and 38.0 percent, respectively. This narrowing of the access gap through a retail-sector subsidy is somewhat surprising, given that Kenya already has a public-sector subsidy for ACTs. But as discussed earlier, illiterate headed households are much less likely to travel to the health center, possibly because they live much closer to the drug shop and are dissuaded by travel costs. Consequently, the public sector subsidy appears to disproportionately reach higher SES households.

5.2.3 Impacts on Targeting

Of course, increasing access will not be beneficial if most of the newly treated illness are not actually malaria. The bottom panels of Figure 6 and Table 3 show ACT take-up rates

by predicted malaria positivity. The subsidy induces a parallel shift in the access curve, suggesting both a large drop in under-treatment and a large increase in over-treatment.

The increase in over-treatment is concentrated among adults, who have a much lower chance of having malaria than children. Recall Figure 1, which presents malaria positivity by age among ACT-takers at the drug shop (solid black line), estimated using the surprise RDT test results in the administrative data. This line presents positivity for ACT-takers in the "AMFm status quo" (92 percent subsidy, no RDT) group. The graph reveals stark differences in over-treatment by age: while patients aged 14 and over tested positive just 39 percent of the time, patients aged 13 and younger tested positive 84 percent of the time.

There does, however, appear to be selection into ACT taking at the drug shop across all ages. The solid gray line shows the positivity rate observed in the symptoms database, which includes illness episodes in the general population irrespective of ACT treatment. This line is significantly below the solid black line. This gap suggests that there is substantial selection into retail sector treatment-seeking. Moreover, much of this selection appears to be on unobservables – the dashed line in Figure 1 plots *predicted* positivity for ACT-takers tested at the drug shop. If selection were largely based on observable symptoms, we would expect this line to be close to the solid black line, but it is clearly not – instead it is close to the positivity rate observed in the generally ill population. The fact that patients who select into ACT taking at the drug shop are more likely to be malaria positive is advantageous from a targeting perspective. But it falls quite short of preventing over-treatment. Overall, the low positivity rate among adult ACT-takers underscores that over-treatment is a major problem when ACTs are heavily subsidized in the retail sector.

Given these results, it is important to ask whether an alternative subsidy policy could achieve significant increases in access among the needy without such a substantial rate of over-treatment. Next we consider two alternatives: (1) Slightly lowering the ACT subsidy level; that is, making ACTs somewhat more expensive, while still heavily subsidized; and (2) making rapid diagnostic tests available at subsidized prices at retail shops.

6 Results: Impacts of Alternative Subsidy Regimes

6.1 Lowering the ACT Subsidy

6.1.1 Sensitivity of ACT Take-Up to ACT Subsidy Level

In this section, we ask whether a subsidy level that is somewhat lower than that targeted by the AMFm might preserve access for the malaria positive while limiting over-treatment. We begin by studying how different ACT subsidy levels (within the range of 80 to 92 percent)

impact retail-sector access. To do so, we use the administrative drug shop data to regress ACT voucher redemption on randomly assigned subsidy levels. This analysis is shown in columns 1-3 of Table 4, Panel A. Column 1 reveals minimal impacts of higher ACT prices on ACT purchases at the drug shop. Decreasing the ACT subsidy level from 92 to 80 percent, which corresponds to increasing the ACT price by 150 percent (from KSh 40 to KSh 100), decreases the share of households using an ACT voucher by only 5.5 percentage points (a decline of 13 percent), which implies a price elasticity of demand of just -0.084 over the subsidy range we consider. This very low price-elasticity over the subsidy range is observed among both illiterate and literate households (see Figure 2).

A comparison of columns 2 and 3 of Table 4, Panel A, reveals strikingly different patterns by age, however. Specifically, households are slightly *more* likely to use an ACT voucher for a child at higher prices, while they are significantly *less* likely to use an ACT voucher for an adult (the implied price elasticity of demand for adults is -0.318). This asymmetry likely reflects the fact that the price of an ACT dose declines with age. Since we only use information on the first voucher redemption, this could generate the appearance of an upward sloping demand curve for doses for young children if households are willing to treat all ages at the high subsidy level, but only young children at the lower subsidy level.[23] Since malaria positivity is substantially higher at younger ages (as are the consequences of an untreated malaria episode), this price selection is advantageous from a targeting perspective. Higher prices help screen out those for whom the expected returns to ACT use are lower: adults.[24]

These results shed light on the impact of price variation on ACT demand *within the retail sector*. However, overall changes in access will depend on public sector crowd-out as well. If the marginal episodes crowded out of the drug shop by a higher price go to the health center and obtain an ACT anyway, then the net impact on access will be zero. In contrast, if the marginal episodes instead do nothing or take a less effective antimalarial, then overall access will decline. To study the overall impact of ACT price variation on access, we exploit our endline data, which includes all illness episodes, irrespective of where they were treated. This analysis is presented in the first three columns of Panel B of Table 4. Although these

[23]This is because in households that treat all ages, some potential voucher redemptions for children will not be observed because the voucher was instead used for an adult. If we assume that households are always willing to treat children if they are willing to treat adults, then the overall price elasticity of demand estimated in the first column will correspond to the price elasticity of demand for young children.

[24]One concern that our study cannot speak to is the impact of higher prices on the share of episodes treated with partial doses. The surveyors who were posted at the drug shops throughout the study period were instructed to never allow the sale of a partial dose to a client. However, drug shop owners often sell partial doses to clients, and it seems likely that this practice would increase at higher ACT prices. Additional research is needed to gauge how common partial dosing is, how it is impacted by ACT price, and how to best prevent it. There are also potentially negative externalities to decreasing access among adults who truly have malaria since this could increase disease transmission.

impacts are less precisely estimated, we obtain similar point estimates and similar patterns of demand by age. This implies that the low-positivity adults screened out by higher prices at the drug shop did not obtain ACTs elsewhere.

6.1.2 Sensitivity of Targeting to ACT Subsidy Level

The last two columns of Table 4 study targeting directly. The sample for this analysis is limited to ACT-takers (those randomly selected for a surprise RDT at the drug shop in Panel A; ACT-takers across all sectors at endline in Panel B). The outcome is a measure of malaria positivity (actual surprise RDT test result in column 4, predicted positivity in column 5). Looking at the administrative data from the drug shop in Panel A, we observe that, even though higher prices do not substantially reduce the share of households seeking treatment they are associated with much higher malaria positivity rates: drug shop ACT-takers are 18-19 percentage points more likely to be malaria-positive under the 88 and 80 percent subsidies than under the 92 percent subsidy. Part of this is due to the selection based on age observed in columns 2 and 3. However, this does not account for the entire selection effect. Adult ACT-takers in the lower subsidy groups are substantially more likely to be malaria positive when compared to adult ACT-takers in the highest subsidy group.[25] The results using predicted positivity instead of actual positivity (column 5) have a similar pattern, but the coefficients are substantially smaller in magnitude. This is not surprising – to the extent that illness episodes selected out of treatment by higher ACT prices have lower observable *and* unobservable indicators of malaria positivity (which seems reasonable based on results in Figure 1), then we will under-estimate the extent to which ACT price improves targeting when using predicted positivity measures.

Column 5 of Panel B presents the analysis using our endline sample of first illness episodes. This analysis provides information on how the retail sector ACT subsidy level affects targeting of ACTs overall, not just of ACTs obtained through the retail sector. Consistent with the access results in column 3, point estimates in column 5 indicate that higher prices increase positivity among ACT-takers overall, though estimates are not uniformly significantly different from zero, possibly due to the aforementioned downward bias introduced by using predicted positivity. We take the positive point estimates as corroborative evidence, and note that since 73-75 percent of all ACT-takers in the three subsidy groups report acquiring the ACTs with a study voucher (and 80 percent report acquiring ACTs from the retail sector), the (unbiased) targeting results using actual positivity at the drug shop (Panel A) can

[25] Adult ACT-takers are 26 and 17 percentage points more likely to test positive in the 88 and 80 percent subsidy groups respectively. Due to the small sample size, only the first estimate is significantly different from 0 (at the 90 percent level).

reasonably be considered as indicative of impacts on overall targeting.

Overall, these results suggest that price is, in this case (as opposed to the case in Cohen and Dupas (2010)), a useful screening tool. Higher prices dissuade adults, who are substantially less likely to have malaria, from purchasing ACTs in the retail sector, and these adults do not simply compensate by acquiring ACTs in the public sector. Importantly, slightly higher prices do not significantly reduce access among those who truly need ACTs – namely, children. However, even at lower subsidy levels 25 percent of ACTs purchased at the drug shop go to malaria-negative patients. This suggests a need for improved access to malaria diagnostics. We now ask whether introducing an RDT subsidy in the retail sector can fill that need.

6.2 Subsidy for Rapid Diagnostic Tests (RDTs)

6.2.1 Impacts of RDT Subsidy on Access to Malaria Testing

The impacts of the RDT subsidy on malaria test taking are presented in Figure 7. Note that the outcome here is whether the illness received any type of malaria test (including microscopy), to account for potential crowd-out of this type of test at the health center. The results are striking: the RDT subsidy nearly doubles the share of illness episodes tested for malaria, from a base of 21.6 percent in the control group up to 42.6 percent. These large impacts reflect a very high willingness to experiment with RDTs in our sample. Among households sampled for the RDT subsidy, over 80 percent of those who sought care at the drug shop chose to take an RDT test before deciding whether or not to purchase an ACT.[26]

6.2.2 Impacts of RDT Subsidy on Targeting of ACT Subsidy

As highlighted by the theory section, RDT provision can impact targeting via the extensive margin (by selecting individuals with different likelihoods of being malaria positive into treatment-seeking at the drug shop) and the intensive margin (individuals who would have gone to the drug shop anyway are now able to view a test result before deciding to purchase an ACT).

Figure 8 presents results on both margins. We plot estimated malaria positivity first among treatment seekers (irrespective of whether they bought an ACT, Panel A) and then specifically among ACT-takers (Panel B).

[26]Despite the high willingness to test, we find no significant evidence that RDTs induced crowd-out from the health center. This suggests that, on average, the RDT subsidy had little impact on access to diagnosis for diseases other than malaria.

Somewhat surprisingly, Figure 8 does not reveal many significant impacts of RDTs on ACT targeting. The only significant difference in the graphs is the positive selection in the retail sector under the 92 percent ACT subsidy level (this is true for both panels A and B). However, there is no clear pattern to how the RDT subsidy interacts with the ACT subsidy level in terms of the extensive margin: Panel A illustrates that, when combined with the highest ACT subsidy level, RDT provision appears to select a pool of individuals who are *more* likely to be malaria positive, whereas at lower subsidy levels, RDTs select a pool of treatment seekers who are *less* likely to be malaria positive. There is no compelling theoretical explanation for this asymmetry, so we interpret the positive retail-sector targeting impact of the RDT subsidy with caution.[27]

The reason why targeting only marginally improved in the RDT subsidy regime is that RDT noncompliance in our population was high. While we explicitly advised that patients aged 5 and under take an ACT regardless of test result (consistent with WHO and Kenyan Ministry of Health guidelines at the time of the study), 49 percent of patients over 5 still took an ACT when RDT negative. This cautiousness in complying with test results is not entirely surprising given the fact that the status quo diagnostic technology is often ignored by health practitioners and has a high rate of false negatives. While RDTs have a much lower rate of false negatives than microscopy (5 percent versus 31 percent, as mentioned above), it might take some time for households to learn this.

Another possible explanation for the high ACT purchase rate after a negative RDT result is hoarding – households might have decided to buy the ACT dose to keep it for later (the next malaria episode). Such hoarding could have been encouraged by the experimental design, if households were afraid the vouchers would expire or that the supply of ACTs at drug shops would dry up. In practice, hoarding did not seem to be common, however, as evidenced by the fact that only 16 percent of households used both vouchers by the end of the study. Nevertheless, to the extent that lack of information and hoarding would disappear in the long run, our results represent a lower bound on RDT compliance (and therefore the targeting benefits of an RDT subsidy).

6.3 Discussion

Taking our point estimates from the endline database at face value, we estimate that reducing the ACT subsidy from 92 to 80 percent and subsidizing RDTs would increase predicted

[27] One possible reason for this result would be if treatment seekers in the 92-percent-ACT-subsidy+RDT group were unusually positive, simply due to chance. A more troubling possibility would be if the 92-percent-ACT-subsidy-only group were unusually malaria negative, simply due to chance. This would lead us to overestimate the targeting impact of RDTs at the 92 percent ACT subsidy level *and* lead us to overestimate the targeting impact of higher ACT prices discussed earlier.

positivity among ACT-takers by 4 percentage points (off of a base of 43 percent) while leaving the share of illness episodes treated with an ACT virtually unchanged. The estimates relying on predicted positivity and may be substantial underestimates, however. The estimates using actual positivity among drug shop clients imply the targeting benefit would be around 24 percentage points (off a base of 56 percent).

How beneficial are these changes and what do they mean for our policy parameters, UT and OT? In our symptoms database, 39 percent of illnesses tested malaria positive. Table 5 combines this with our estimates of A and T to illustrate the exent of under- and over-treatment under three regimes of interest: the AMFm "status quo", an 80 percent ACT subsidy with no RDT, and an 80 percent ACT subsidy with an RDT subsidy. Since our predicted positivity targeting estimates are likely biased down, we use drug shop targeting estimates for ACTs acquired at the drug shop and illustrate three scenarios with different assumed targeting rates at the health center.[28] Over-treatment decreases monotonically from one regime to the next, reflecting the combined effect of increased targeting and small declines in access. Interestingly, under-treatment also decreases as the ACT subsidy level decreases. This result is the direct consequence of our finding that ACT access does not meaningfully decrease when the subsidy level decreases, but targeting substantially improves. Mechanically, this implies that under-treatment must go down. Thus what seems to be happening is a reallocation (within the household) of resources from non-malaria episodes to malaria episodes. In other words, when the ACT price is higher, it deters households from treating illness episodes that have a low malaria probability, and the resources saved can be used to treat illness episodes with a higher malaria probability. Likewise, resources that are not spent on ACTs after a negative RDT can be spent on other episodes.The targeting benefits of the alternative subsidy regimes are illustrated visually in Figure 9. The alternative regimes steepen the access-predicted positivity gradient, increasing use among appropriate users while decreasing use among inappropriate users. Overall, given the partial adherence to RDT results that we observe, an ACT+RDT subsidy regime performs only slightly better in terms of T, UT and OT than the non-RDT regimes. Therefore the gains may not be enough to justify the cost of the RDT subsidy: the 80 percent ACT subsidy with no RDT subsidy performs almost as well in terms of targeting as compared to the same subsidy level plus an RDT subsidy, but costs 29 percent less per illness episode.

This does not imply that RDTs do not have the potential to be cost effective. As discussed earlier, there are reasons to think that RDT compliance would improve over time, provided people learn about their accuracy. What's more, an important benefit of RDTs that is not captured by our calculations is that they may increase the likelihood that a non-malaria

[28]Recall that when overall malaria prevalence is Π, $UT = 1 - TA/\Pi$ and $OT = A(1-T)/(1-\Pi)$.

illness is treated with appropriate medication promptly. Given that pneumonia, a bacterial illness, is the largest cause of childhood mortality, this benefit could be substantial, even if individuals who test RDT negative continue to take ACTs as a precaution.

RDT results may also help households learn about the effectiveness of ACTs: if an illness doesn't get better after taking an ACT, the household might not use this a signal that ACTs are ineffective if the RDT test was negative. This effect could be very important. Adhvaryu (2011) presents evidence from Tanzania suggesting that individuals are more likely to go seek free ACTs at their local health center when the rate of over-treatment with ACTs in their neighborhood in the previous 6 weeks was lower. This is consistent with a model in which households interpret non-recovery among ACT-takers as a negative signal about the effectiveness of ACTs, rather than revise the diagnosis. Expanding access to accurate diagnosis could greatly reduce this type of incorrect inference.

Our finding that many households are willing to pay for an RDT even if they plan to take an ACT regardless of the result suggests that households do see some of these important benefits to testing. What's more, our data suggests that exposure to RDTs fosters future RDT adoption. We find evidence that, among those households that did not take-up the RDT at their first drug shop visit, those sampled for a "surprise RDT" were more likely to redeem an RDT voucher at their revisit, compared to those not exposed to a surprise RDT (see Table A5, column 1). Moreover, a geographical analysis of redemption patterns in our data shows that exposure to RDTs via neighbors increased demand for RDTs over the course of the study, suggesting important social learning effects (see Table A5, column 2). Learning to fully *trust* the RDT result might take much longer, however, and it is likely to require much greater exposure (for example, allowing each patient to take two RDTs for a given illness, to help demonstrate the consistency of the test). Further research is needed to assess the long-run impact of expanding access to rapid diagnostic testing.

6.4 External Validity

Piloted as a "global subsidy", the AMFm is a somewhat blunt policy tool, implemented uniformly nationwide in countries as diverse as Madagascar, Tanzania and Nigeria. Our study clearly shows that the subsidy's impact will depend a great deal on where households seek care, baseline access to ACTs, baseline access to diagnostic testing, and households' ability to gauge their malaria status. A key question is therefore whether our findings apply outside of our specific study context. A review of data from other malaria endemic areas suggests that the answer is yes. While our study was carried out in only one region of Kenya, the malaria treatment seeking environment in our study is similar to a wide swath of the

heavy malaria-burden regions in sub-Saharan Africa. Table 6 presents basic statistics from household surveys conducted in two regions of Uganda, two regions of Tanzania and the Southern region of Malawi.[29]

As seen in Western Kenya, these surveys reflect heavy reliance on the private/retail sector for malaria treatment, limited use of ACTs to treat malaria episodes and high out of pocket expenditures on (frequently experienced) malaria episodes. All surveys reveal limited rates of blood test diagnosis for suspected malaria episodes, and the Uganda studies show a similar malaria-age gradient to the one found here, with the rate of positivity among adults roughly double the rate among children. These striking similarities suggest that our targeting results may be generalizable across regions. In fact, in the Central Uganda study, which included RDT results among patients buying subsidized ACTs at drug shops, the observed rate of over-treatment among adults is extremely similar to that observed in Western Kenya during our study, with less than half of adults taking subsidized ACTs testing positive for malaria. Finally, data that we collected from our study households in 2011, a year after the AMFm pilot subsidy was introduced in Kenya, confirms that targeting is indeed a major problem at the AMFm subsidy level: just 45 percent of patients who recently took ACTs tested positive for malaria.

7 Conclusion

There is a large class of health issues for which both under-treatment and over-treatment generate negative spillovers. Under-treatment is a public bad for any communicable disease, since the number of untreated individuals increases transmission rates. Over-treatment is a public bad whenever the cost of treatment is subsidized. Over-treatment is also a public bad when it leads to drug resistance. For this class of health issues, it is critical to find the right balance between, on the one hand, access and affordability when the medicine is truly needed, and on the other hand, disincentive to overuse the medicine.

Malaria is one of the most common (and deadly) illnesses in this class of health issues, killing close to 1 million people each year, partly because of lack of access to effective treatment. At the same time, parasite resistance to treatment has been developing faster and faster with each new generation of antimalarials. Learning how to reduce malaria mortality and morbidity through prompt access to effective treatment, while at the same time limiting

[29]The surveys covered rural areas, town centers and some small urban areas, but did not include major cities. The surveys were conducted 1.5-2 years after the baseline survey conducted for this study. The data in columns (2) and (3) are from surveys that took place one month and three months into the AMFm launch in Uganda and Tanzania, respectively, but in both cases a limited quantity of subsidized ACTs had arrived in country at that time.

resistance to the latest generation of antimalarials, the ACT, is one of the most pressing and important questions facing the global health community today.

This paper is a step forward in the direction of answering this question. We use detailed data on treatment-seeking behavior of over 2,700 households in a malaria-endemic area of Kenya, combined with an innovative experimental design to identify essential pieces of the puzzle: the price elasticity of demand for effective medication, how demand for ACTs varies by malaria risk level, and how access to proper diagnosis affects the demand for medication and targeting. Our analysis leads to four important findings.

First, we find that the demand for ACTs is very low at unsubsidized prices, but substantial and inelastic over a range of subsidized prices. This suggests that subsidies for ACTs are clearly needed to increase ACT access among those that suffer from malaria, but these subsidies may not need to be as large as currently planned by the donor community. Second, we find that over-treatment of malaria is extremely common; therefore large ACT subsidies alone would lead to an important increase in inappropriate use of ACTs. Third, we find evidence that price is a useful tool for selection: somewhat higher ACT prices reduce ACT taking among adults, who are substantially less likely to be malaria positive, while leaving access among children unchanged. Fourth, we find that demand for rapid diagnostic testing is extremely high when it is readily affordable and available. However, compliance with the test results would need to increase for diagnostic testing to substantially improve ACT targeting. This short-run result is not entirely surprising: households face a fairly complicated inference problem, with uncertainty regarding not only which of their illness episodes are truly malaria, but also how effective different antimalarials are, and how reliable diagnostic tests are. Enabling cheaper and joint experimentation with ACTs and RDTs through a bundled subsidy could facilitate household learning about these various parameters. Additional research is needed to understand how best to facilitate learning under a bundled subsidy regime.

Moreover, many questions regarding the supply side of the subsidy policy remain unanswered. For example, drug shops, which make a profit from selling antimalarials whether their clients are truly malaria positive or not, might not have any incentive to sell a cheap diagnostic test that will result in fewer drug purchases – their incentives would depend on the relative profit margins associated with antimalarials and RDTs and underlying malaria endemicity (Cohen and Dickens 2012). The problem of RDT provision is thus an incentive problem similar to that of "informed experts" who sell both their diagnostic of a problem and the solution to the problem, such as surgeons or auto repair shops (Wolinsky 1993). Future research on optimal provider incentives and other supply side issues is needed to support further innovations in malaria subsidy policy.

References

Adhvaryu, A. R. (2011). Learning, Misallocation, and Technology Adoption: Evidence from New Malaria Therapy in Tanzania. Mimeo.

Arnold, F., Y. Ye, R. Ren, S. Yoder, K. Hanson, C. Goodman, S. Tougher, A. Mann, and B. Willey (2012). Independent Evaluation of Phase 1 of the Affordable Medicines Facility - malaria (AMFm): Preliminary Report. Technical report.

Arrow, K., C. Panosian, and H. Gelband (Eds.) (2004). *Saving Lives, Buying Time: Economics of Malaria Drugs in an Age of Resistance*. Washington, DC: Institute of Medicine: National Academies Press.

Ashraf, N., J. Berry, and J. M. Shapiro (2010). Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia. *American Economic Review 100*(5), 2383–2413.

Banerjee, A., A. Deaton, and E. Duflo (2004). Health Care Delivery in Rural Rajasthan. *Economic and Political Weekly 39*(9).

Bjorkman, M., J. Svensson, and D. Yanagizawa-Drott (2012). Can Good Products Drive Out Bad? Experimental Evidence from Local Markets for Antimalarial Medicine in Uganda. *Working Paper*.

CDC (2011). About Malaria. http://www.cdc.gov/malaria/about/disease.html. Accessed April 14, 2011.

Chaudhury, N., J. Hammer, M. Kremer, K. Muralidharan, and F. H. Rogers (2006). Missing in Action: Teacher and Health Worker Absence in Developing Countries. *The Journal of Economic Perspectives 20*(26), 91–116.

Cohen, J. and W. Dickens (2012). Adoption of Over-the-Counter Diagnostics in Africa: The Role of Subsidies, Beliefs, Externalities and Competition. In L. R and M. MK (Eds.), *The Value of Information: Methodological Frontiers and New Applications in Environment and Health*. Springer Press.

Cohen, J. and P. Dupas (2010). Free Distribution or Cost-Sharing? Evidence from a Randomized Malaria Prevention Experiment. *The Quarterly Journal of Economics 125*(1), 1–45.

Das, J., J. Hammer, and K. Leonard (2008). The Quality of Medical Advice in Low-Income Countries. *The Journal of Economic Perspectives 22*(2), pp. 93–114.

de Oliveira, A. M., J. Skarbinski, P. O. Ouma, S. Kariuki, J. W. Barnwell, K. Otieno, P. Onyona, L. M. Causer, K. F. Laserson, W. S. Akhwale, L. Slutsker, and M. Hamel (2009). Performance of malaria rapid diagnostic tests as part of routine malaria case management in kenya. *Am J Trop Med Hyg 80*(3), 470–474.

Dupas, P. (2011). Health Behavior in Developing Countries. *Annual Review of Economics 3*, 425–449.

Dupas, P. (2012). Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment. Working Paper 16298, National Bureau of Economic Research.

Gertler, P. and J. Hammer (1997). Strategies for Pricing Publicly Provided Health Services. *Policy Research Working Paper 1762. Wold Bank, Washington D.C.*

Global Fund to Fight AIDS, TB and Malaria (2010). AMFm Frequently Asked Questions. Technical report.

Griffin, C. (1987). User charges for health care in principle and practice. *Economic Development Institute, Seminar Paper No. 37, The World Bank, Washington DC.*

Hoffmann, V. (2009). Intrahousehold Allocation of Free and Purchased Mosquito Nets. *American Economic Review 99*(2), 236–41.

Juma, E. and D. Zurovac (2011). Changes in Health Workers' Malaria Diagnosis and Treatment Practices in Kenya. *Malaria Journal 10*(1), 1.

Kangwana, B. B., J. Njogu, B. Wasunna, S. V. Kedenge, D. N. Memusi, C. A. Goodman, D. Zurovac, and R. W. Snow (2009). Short Report: Malaria Drug Shortages in Kenya: A Major Failure to Provide Access to Effective Treatment. *American Journal of Tropical Medicine and Hygiene 80*(5), 737–738.

Kenya Division of Malaria Control (2011). Kenya Malaria Fact Sheet. http://www.nmcp.or.ke/section.asp?ID=4. Accessed May 4, 2011.

Kremer, M., J. Leino, E. Miguel, and A. Zwane (2011). Spring Cleaning: Rural Water Impacts, Valuation, and Property Rights Institutions. *The Quarterly Journal of Economics 126*(1).

Leonard, K. L. (2007). Improving Health Outcomes by Choosing Better Doctors: Evidence of Social Learning about Doctor Quality from Rural Tanzania. Mimeo.

Leonard, K. L. (2009). The Cost of Imperfect Agency in Health Care: Evidence from Rural Cameroun. *Journal of Development Economics 88*(2), 282 – 291.

Leonard, K. L., G. R. Mliga, and D. H. Mariam (2002). Bypassing Health Centers in Tanzania: Revealed Preferences for Observable and Unobservable Quality. *Journal of African Economies 11*(4). Mimeo.

Marsh, V. M., W. M. Mutemi, A. Willetts, K. Bayah, S. Were, A. Ross, and K. Marsh (2004). Improving Malaria Home Treatment by Training Drug Retailers in Rural Kenya. *Tropical Medicine & International Health 9*(4), 451–460.

McGuire, T. G. (2000). Chapter 9: Physician Agency. Volume 1, Part 1 of *Handbook of Health Economics*, pp. 461 – 536. Elsevier.

Olmstead, T. and R. Zeckhauser (1999). The Menu-Setting Problem and Subsidized Prices: Drug Formulary Illustration. *Journal of Health Economics 18*(5), 523 – 550.

Patouillard, E., K. Hanson, and C. Goodman (2010). Retail Sector Distribution Chains for Malaria Treatment in the Developing World: A Review of the Literature. *Malaria Journal 9*(1), 50.

Perkins, M. and D. Bell (2008). Working Without a Blindfold: The Critical Role of Diagnostics in Malaria Control. *Malaria Journal 7*(Suppl 1), S5.

Reyburn, H., R. Mbatia, C. Drakeley, I. Carneiro, E. Mwakasungula, O. Mwerinde, K. Saganda, J. Shao, A. Kitua, R. Olomi, B. Greenwood, and C. Whitty (2004). Overdiagnosis of Malaria in Patients with Severe Febrile Illness in Tanzania: A Prospective Study. *British Medical Journal 329*(7476), 1212.

Shretta, R., J. Omumbo, B. Rapuoda, and R. Snow (2008). Using evidence to change antimalarial drug policy in kenya. *Trop Med Int Health 5*, 755–764.

Tarozzi, A., A. Mahajan, B. Blackburn, D. Kopf, L. Krishnan, and J. Yoong (2011). Micro-loans, Insecticide-Treated Bednets and Malaria: Evidence from a randomized controlled trial in Orissa (India). Mimeo.

Terlouw, D. J., B. L. Nahlen, J. M. Courval, S. K. Kariuki, O. S. Rosenberg, A. J. Oloo, M. S. Kolczak, W. A. Hawleya, A. A. Lal, and F. O. ter Kuile (2003). Sulfadoxine-Pyrimethamine in Treatment of Malaria in Western Kenya: Increasing Resistance and Underdosing. *47(9)*, 2929–2932.

Welch, H. G., L. M. Schwartz, and S. Woloshin (2011). *Overdiagnosed: Making People Sick in the Pursuit of Health*. Beacon Press.

White, N. (2004). Antimalarial drug resistance. *J Clin Invest. 113*(8), 1084–1092.

Wolinsky, A. (1993, Autumn). Competition in a Market for Informed Experts' Services. *RAND Journal of Economics 24*(3), 380–398.

World Bank (2004). World Development Report 2004: Making Services Work for Poor People. Technical report.

World Health Organization (2009). World Malaria Report. Technical report, World Health Organization.

World Health Organization (2010a). Guidelines for the Treatment of Malaria. Technical report.

World Health Organization (2010b). Malaria Rapid Diagnostic Test Performance. Technical report.

Zurovac, D., B. Midia, S. A. Ochola, M. English, and R. W. Snow (2006). Microscopy and Outpatient Malaria Case Management among Older Children and Adults in Kenya. *Tropical Medicine & International Health 11*(4), 432–440.

Appendix: Predicting Malaria Positivity

We impute malaria probabilities to endline illness episodes based on the following probit model, fit to our symptoms database:

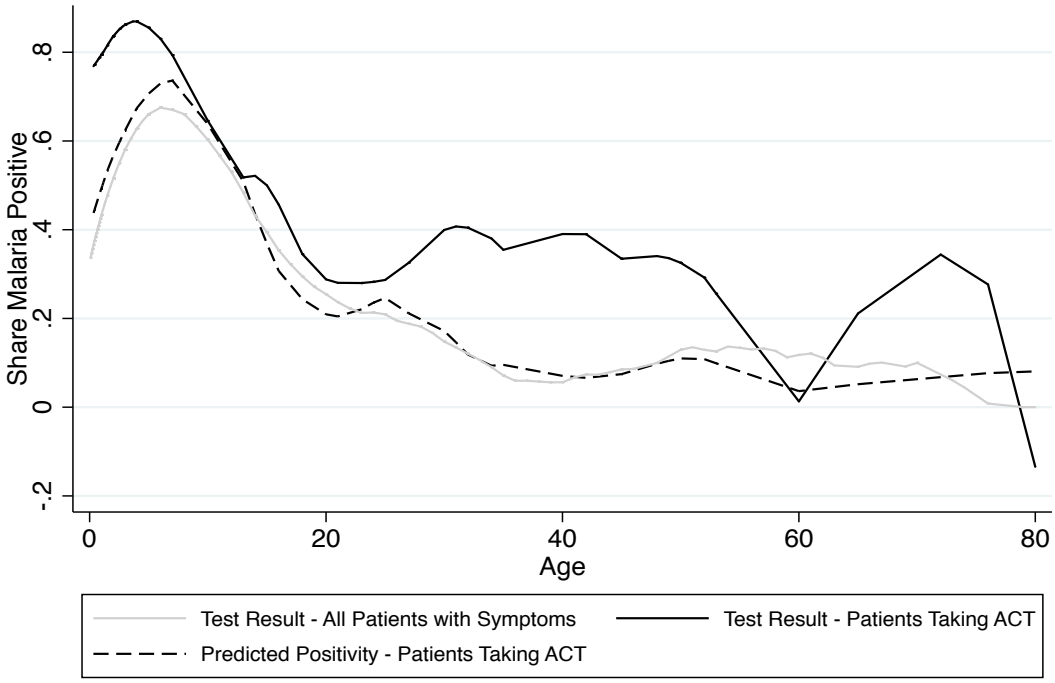
$$\Pr\left(pos_{eh} = 1 \mid x_{eh}, over14_{eh}\right) = \Phi\left(\beta_0 + x'_{eh}\delta + over14_{eh}\lambda + \left(x \times over14\right)'_{eh}\gamma\right)$$

where pos_{eh} is a dummy variable equal to 1 if illness episode e experienced by household h in our symptoms database tested RDT positive for malaria, x_{eh} is a vector of illness characteristics including patient age and age squared, as well as symptom dummies (cough, chills, headache, diarrhea, runny nose, vomiting, body pain, malaise/fatigue, and poor appetite), and $over14_{eh}$ is a dummy variable indicating that the patient is aged 14 or older (i.e. requires an "adult" dose; see Figure A1). We also interact all the symptom dummies with this indicator, to allow for a different relationship between malaria positivity and symptoms among younger and older patients.[30]

The results of this regression are presented in Appendix Table A3. Our estimates are consistent with clinical indicators of malaria (CDC 2011) – chills, headaches, and body pain are positively correlated with malaria positivity, while runny nose is negatively correlated with malaria positivity. Table A3 also reveals that age correlates very strongly with malaria positivity. Although the interaction terms make the trend somewhat difficult to infer, sick children (aged 13 and under) are substantially more likely to actually have malaria as compared to sick adults (the relevant fractions testing positive are 14 percent for adults and 58 percent for children). Figure 1 illustrates the strength of this relationship graphically by presenting local linear regression results of actual malaria positivity on patient age for patients aged 80 and younger tested in our symptoms database (gray line). While striking, these results are not unexpected – young children are substantially more vulnerable to malaria, as they do not benefit from the acquired immunity that develops with repeated exposure to the parasite.

[30]We do not include the most commonly cited symptom of malaria, fever, in order to avoid endline reporting bias. In Kiswahili (the interview language for our respondents), the word for "fever" – "*homa*" – is commonly used to refer to malaria. A concern is that if the subsidy regimes we study affected the likelihood that people get a formal diagnosis, this would make the reporting of *homa* (hence fever) endogenous. The pseudo R^2 on the probit declines from 0.2308 to 0.2216 when excluding fever and its interaction with the age variables. In practice, our results are very similar when including fever in predicting malaria positivity (though including fever does appear to introduce some reporting bias).

Figure 1. Actual and Predicted Malaria Positivity by Age and Treatment-Seeking Status

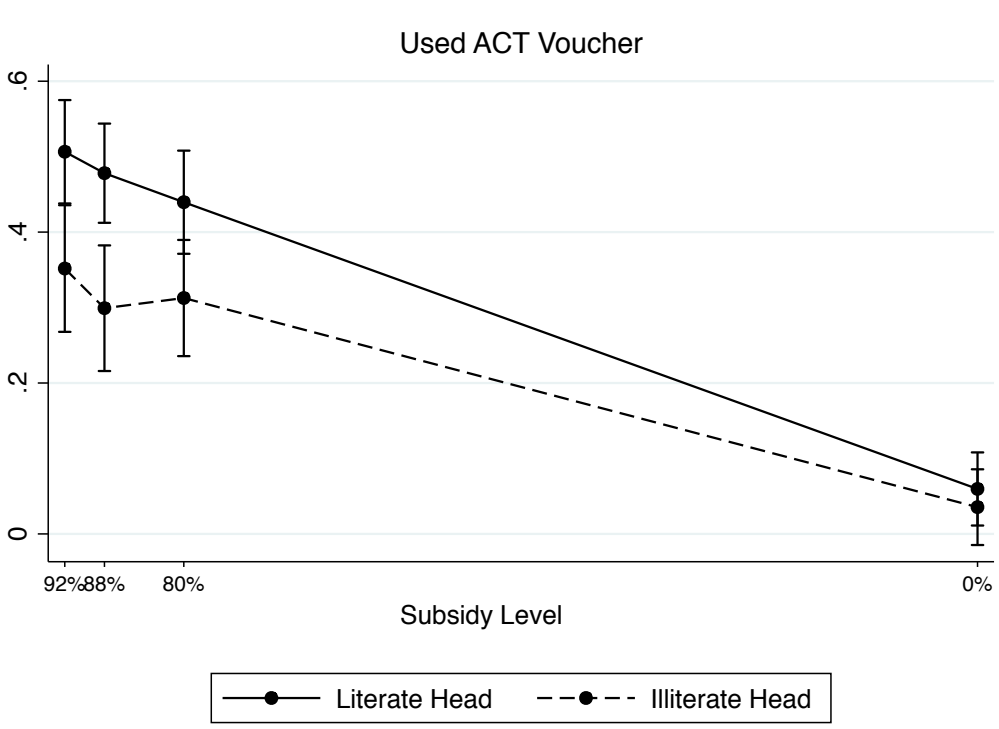


Notes: Local linear regression results for patients aged 80 and younger. The breakdown by SES is shown in Figure A2.

"Test Result" is a 0/1 malaria status variable that comes from rapid malaria diagnostic tests administered by trained enumerators to patients visited at home within 3 days of the start of an illness (grey line, source: symptoms database), or to surprise tested patients for whom a 92% subsidy ACT was purchased at the drug shop (solid black line, source: drug shop transactions data).

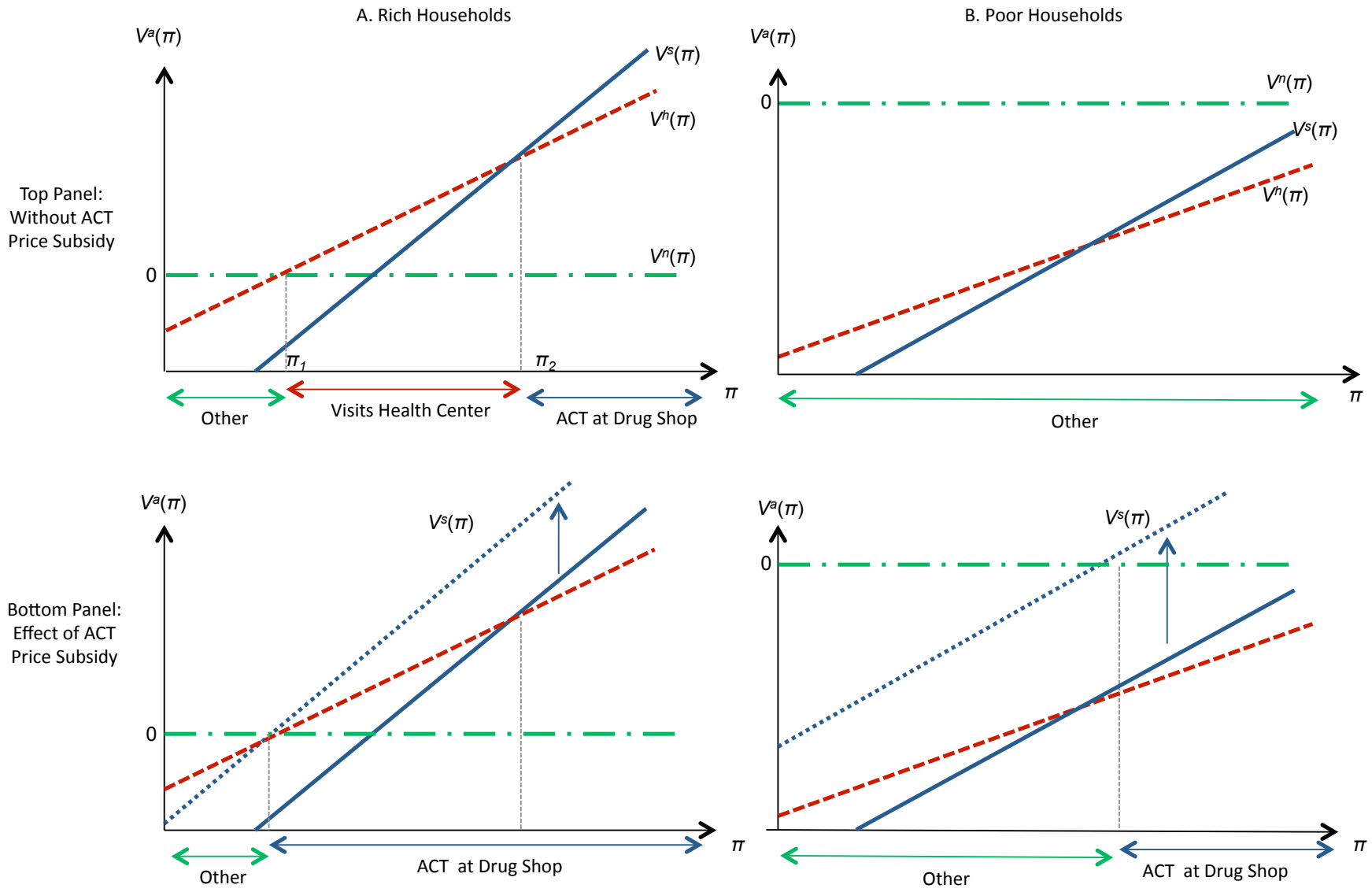
"Predicted Positivity" is a variable between 0 and 1 that is imputed based on reported symptoms (see appendix for details). The dashed line shows the average predicted positivity by age group for the same set of patients as the solid black line. The gap between these two lines correspond to selection into treatment based on unobservables.

Figure 2. Subsidy-Level Sensitivity of the Demand for Retail-Sector ACTs



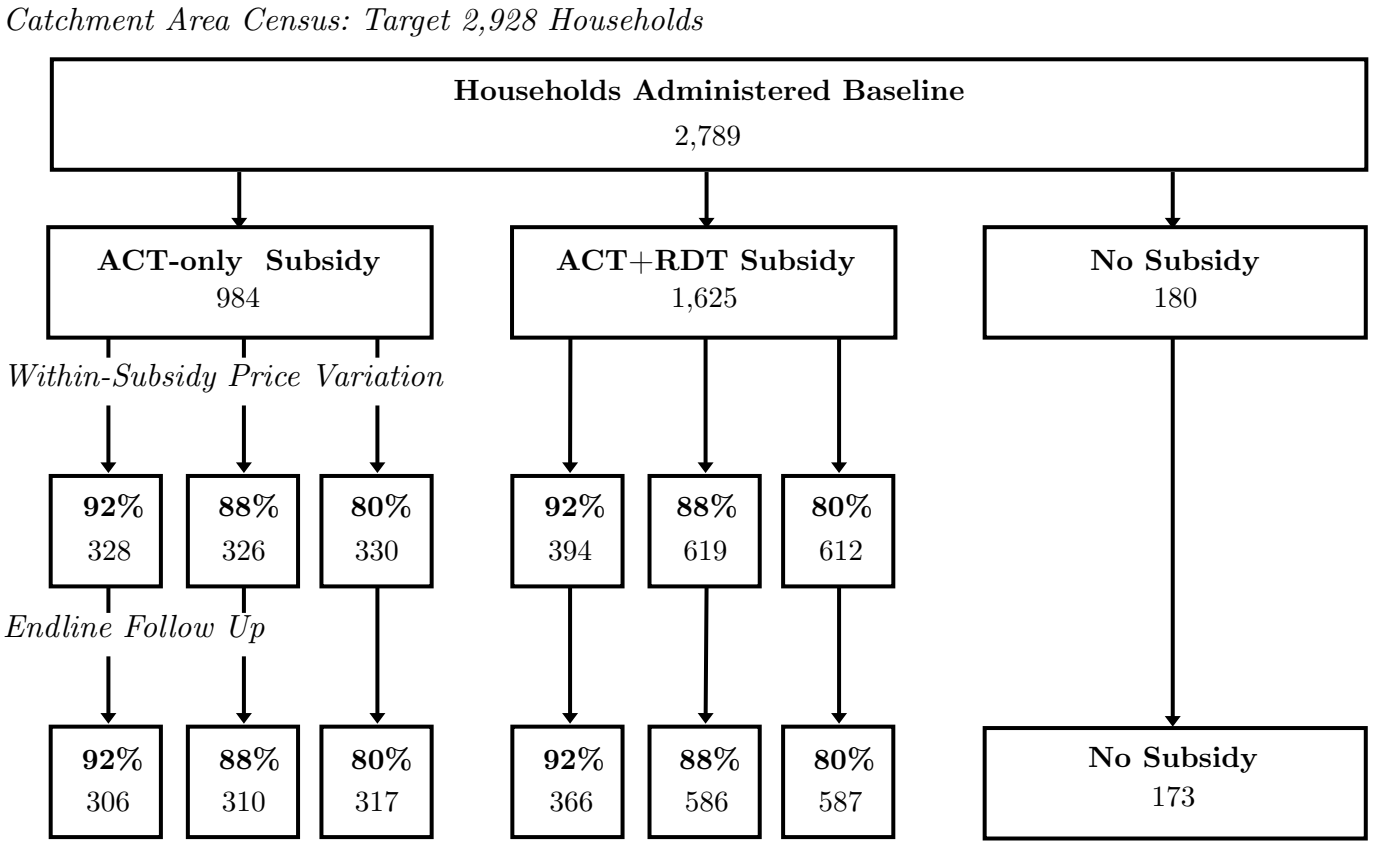
Notes: Figure plots predicted values and 95 percent confidence intervals from regression estimates using heteroskedasticity robust standard errors. 92%, 88% and 80% subsidies correspond to 40Ksh ($0.50), 60 Ksh ($0.75) and 100 Ksh ($1.25) for an adult dose, respectively. Regressions include controls for age of the household head, RDT treatment, and strata. These variables are evaluated at sample means when calculating predicted values.

Figure 3. Theoretical Treatment Seeking Scenarios



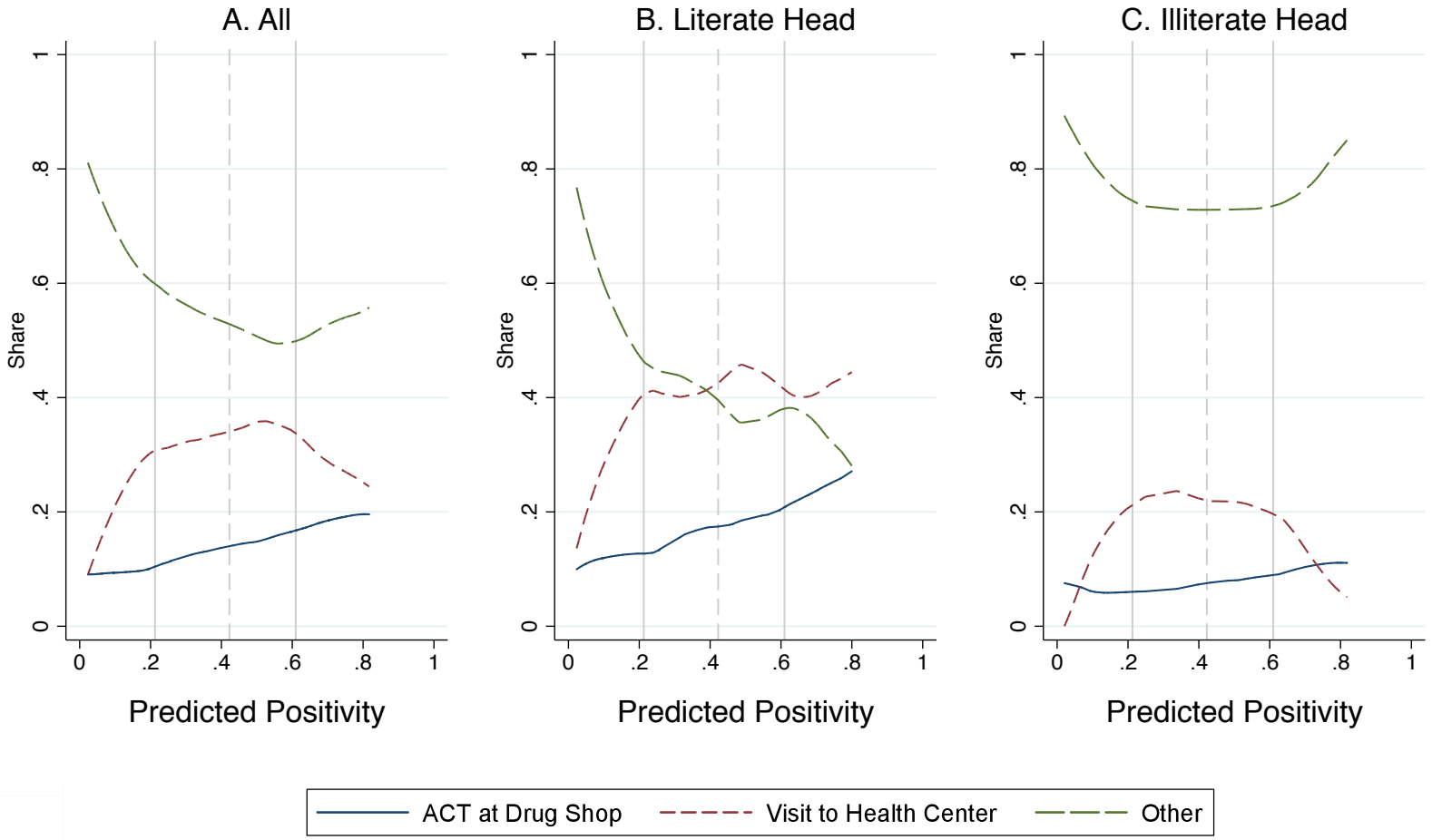
Notes: π is the (perceived and actual) probability that the illness episode is malaria. V^s is the value of purchasing an ACT at the drug shop; V^h is the value of visiting a health center and receiving free ACT if positive; V^n is the value of doing neither of the two options above. The value functions are normalized so that $V^n(\pi)=0$ for all π.

Figure 4. Experimental Design and Attrition: Number of Households per Study Arm



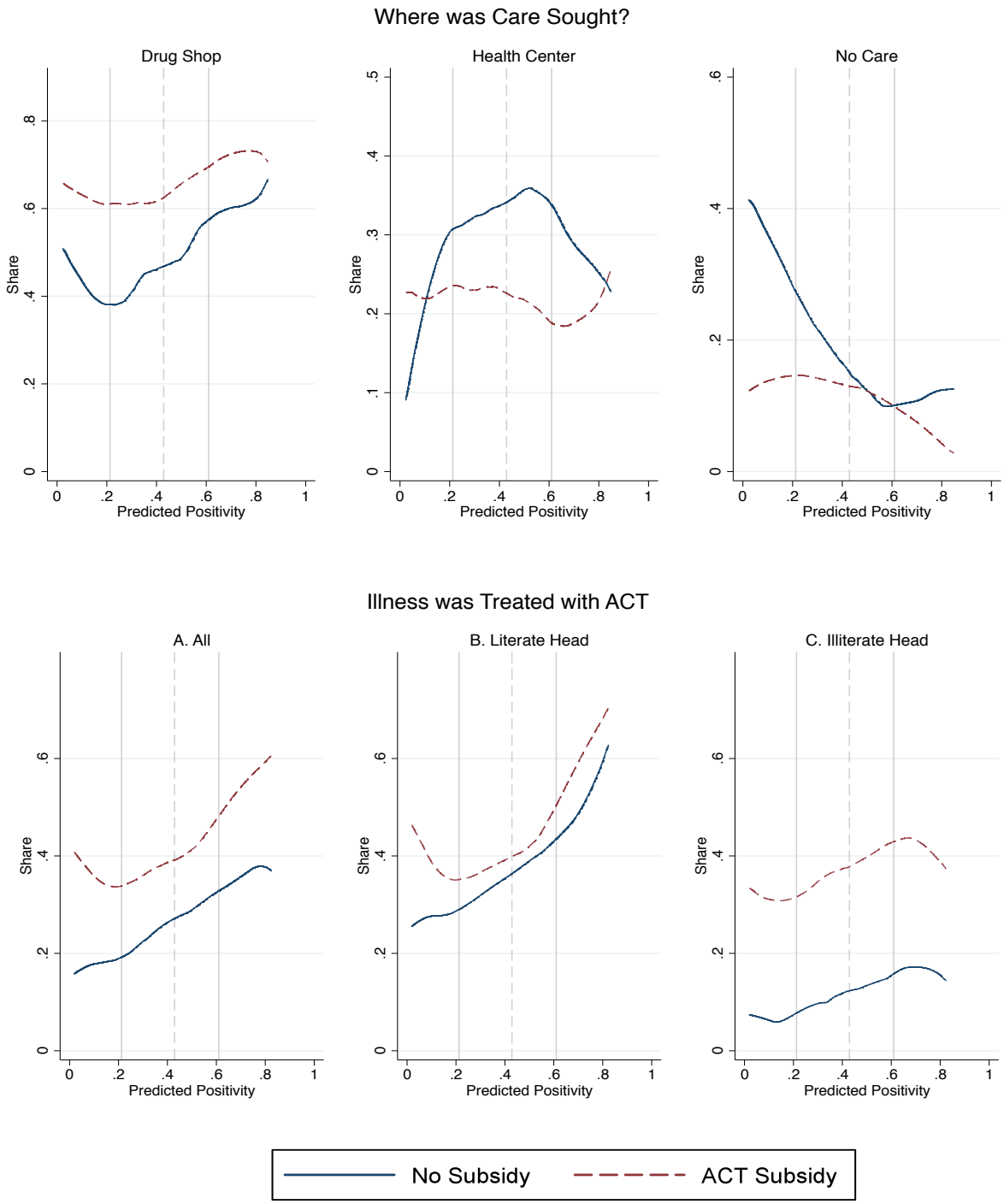
Notes: 49 percent of ACT-only subsidy households and 80 percent of ACT+RDT subsidy households were selected for surprise RDT testing at the drug shop. Within each ACT subsidy level, those in the ACT+RDT subsidy group were also randomized into three RDT subsidy levels. Since we find no differences across RDT subsdidy levels, we lump them together for simplicity. Details for the impact of the RDT subsidy are provided in Table A4.

Figure 5. Baseline Malaria Treatment Seeking Behavior by Predicted Positivity and Literacy of Household Head



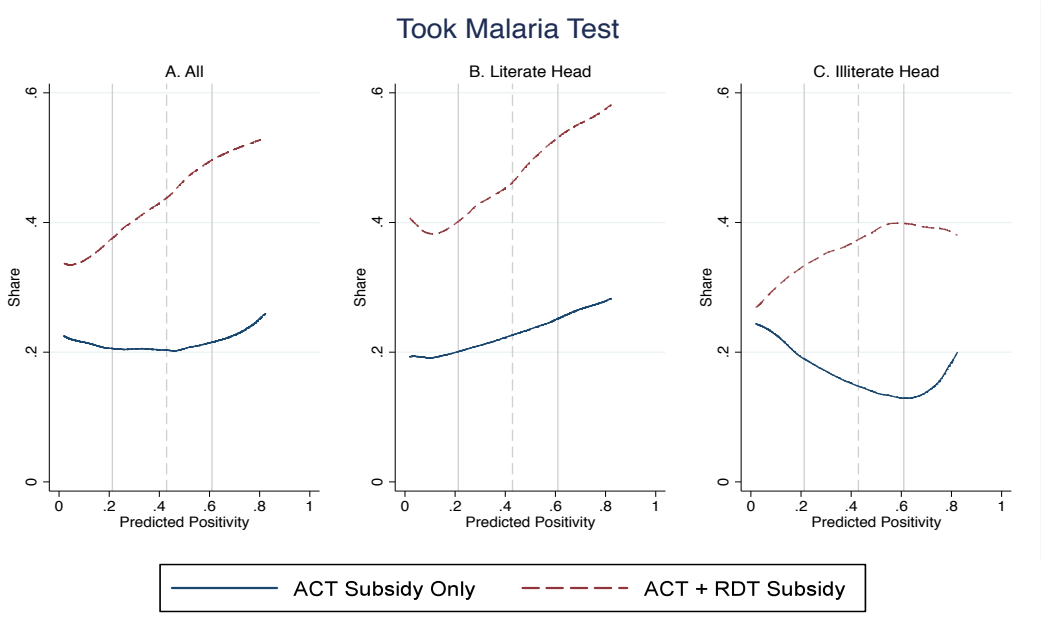
Notes: Data from "No Subsidy" group. Local linear regression lines trimmed at 2.5 percent. Tertiles demarcated by gray vertical lines. Median demarcated by dashed gray vertical line.

Figure 6. Impact of Retail Sector ACT Subsidy on Provider Choice and ACT Access



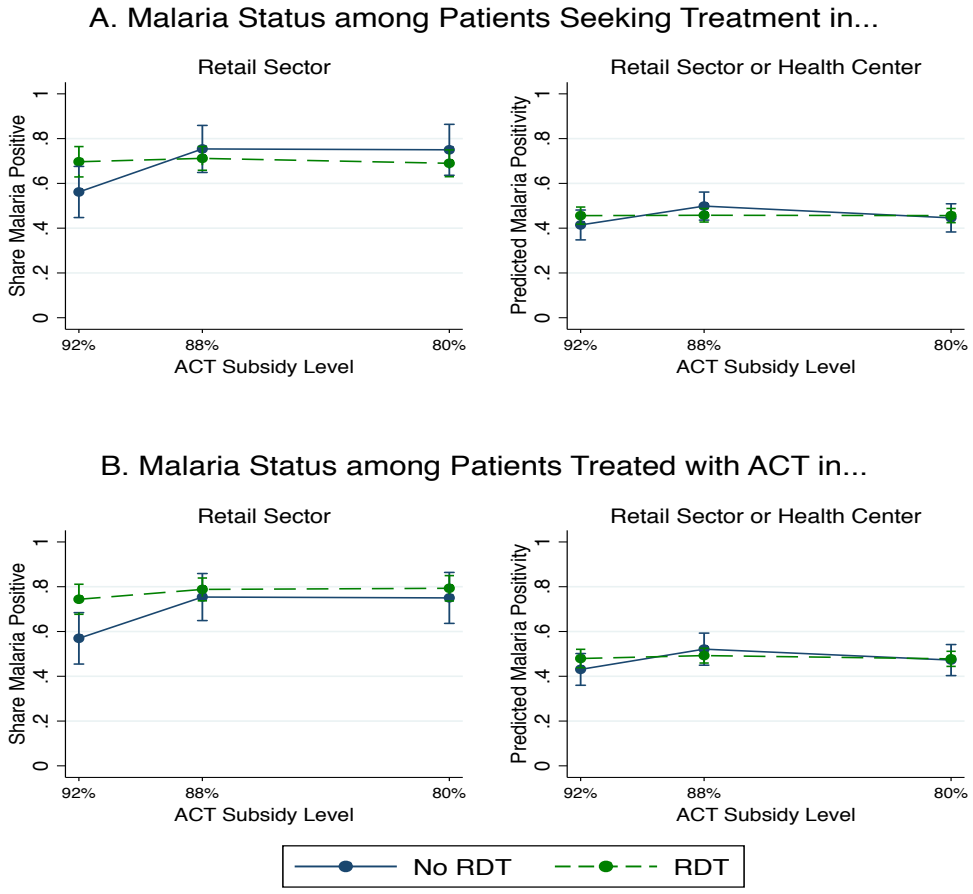
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Dashed gray vertical line shows median. Excludes households randomly selected for surprise RDT testing at drug shop.

Figure 7. Impact of Retail Sector RDT Subsidy on Malaria Testing



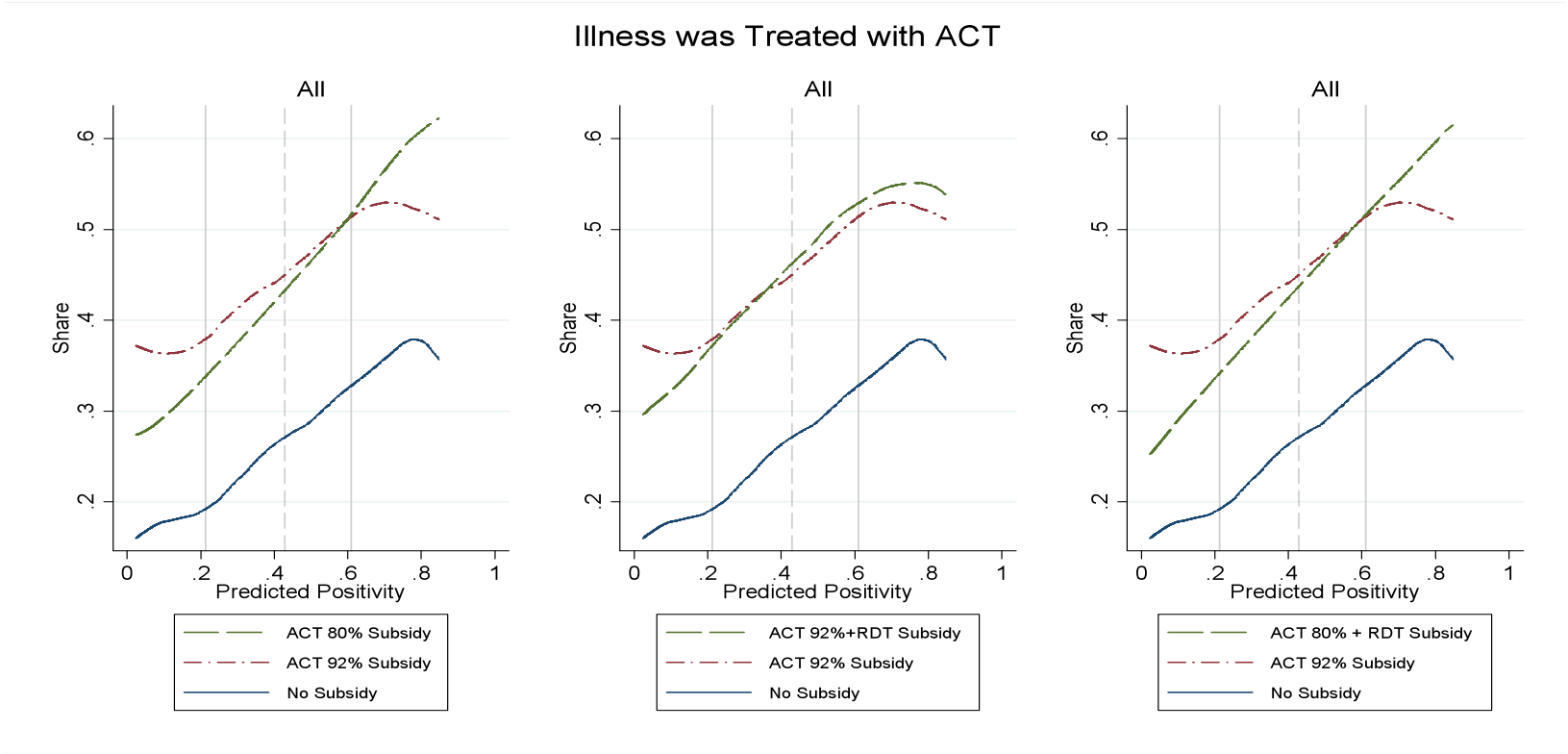
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Dashed gray vertical line shows median. Excludes households without RDT vouchers that were randomly selected for surprise RDT testing at drug shop.

Figure 8. Impact of Retail Sector RDT Subsidy on Share of ACT Takers Who Are Malaria Positive



Notes: Whiskers denote 95 percent confidence intervals on regression coefficients estimated with robust standard errors clustered at the household level (when relevant). Left column graphs based on administrative data collected at drug shops; use actual malaria status (from surprise RDT) as the outcome. Right column graphs based on endline survey data; include first illness episode for each household and use predicted positivity (based on symptoms) as the outcome.

Figure 9. Targeting Across Subsidy Regimes



Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Dashed gray vertical line shows median. Excludes households randomly selected for surprise RDT testing at drug shop.

Table 1. Summary Statistics

		Difference vs. Control:					
	Control Group (C)	ACT Subsidy Only (T1-C)	ACT Subsidy + RDT Subsidy (T2-C)	P-value (C=T1)	P-value (C=T2)	P-value (T1=T2)	N
Characteristics of Interviewed Household Head							
Female	0.867	0.028	0.040	0.291	0.128	0.351	2789
Age (years)	41.7	-2.54	-2.43	0.066*	0.072*	0.862	2646
Education (years)	5.10	0.224	0.405	0.489	0.198	0.260	2774
Literate	0.575	0.041	0.041	0.298	0.292	0.968	2782
Married	0.783	-0.002	-0.015	0.962	0.634	0.400	2784
Subsistence Farming is Primary Occupation	0.589	0.050	0.044	0.210	0.253	0.768	2787
Number Dependents	4.12	-0.147	-0.109	0.488	0.599	0.697	2663
Household Characteristics							
Number members	5.48	-0.261	-0.225	0.204	0.263	0.694	2789
Fraction Adults (Ages 14+)	0.623	-0.036	-0.034	0.052*	0.056*	0.860	2337
Acres Land	2.72	-0.611	-0.407	0.052*	0.206	0.079*	2250
Distance from drug shop (km)	1.68	0.009	0.018	0.676	0.375	0.373	2788
Distance from closest clinic (km)	6.57	-0.032	0.010	0.564	0.855	0.109	2785
Baseline Malaria Knowledge and Health Practices							
Number bednets	1.77	-0.021	-0.015	0.855	0.894	0.915	2784
Share HH members slept under net	0.561	0.020	0.007	0.539	0.812	0.452	2661
Heard of ACTs	0.399	0.021	0.022	0.588	0.554	0.951	2771
Heard of RDTs	0.128	0.027	0.014	0.333	0.596	0.370	2786
Treats water regularly	0.408	-0.017	0.009	0.671	0.820	0.193	2779
Number of presumed malaria episode last month	1.20	-0.007	0.023	0.940	0.809	0.542	2789
Cost per Episode (Among Those Seeking Care)							
Total Cost (US $)	1.63	-0.036	0.066	0.873	0.780	0.559	1319

Notes: The first column shows average values of characteristics for the control group. The second column shows differences between treatments and control when regressing the characteristic of interest on treatment dummies and a full set of strata dummies. P-values are based on heteroskedasticity robust standard errors. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively. The exchange rate at the time of the study was around KSh78 to US$1.

Table 2. Impact of ACT Subsidy on Treatment Seeking by Literacy and Predicted Malaria Positivity

	All			Literate			Illiterate		
	Sought Care at Drug Shop	Sought Care at Health Center	Sought No Care	Sought Care at Drug Shop	Sought Care at Health Center	Sought No Care	Sought Care at Drug Shop	Sought Care at Health Center	Sought No Care
Specification 1 - Main Effect									
α ACT Subsidy	0.159***	-0.076*	-0.091***	0.215***	-0.135**	-0.085**	0.072	0.002	-0.096
	(0.047)	(0.043)	(0.036)	(0.061)	(0.059)	(0.043)	(0.074)	(0.056)	(0.061)
Specification 2 - Impact by Predicted Malaria Positivity									
α_1 ACT Subsidy×Lower Tertile	0.144*	0.056	-0.206***	0.272***	0.009	-0.286***	-0.027	0.115	-0.108
	(0.081)	(0.072)	(0.074)	(0.109)	(0.103)	(0.096)	(0.130)	(0.095)	(0.118)
α_2 ACT Subsidy×Middle Tertile	0.220**	-0.225***	0.000	0.225*	-0.238**	0.004	0.205	-0.177	-0.028
	(0.100)	(0.093)	(0.074)	(0.124)	(0.121)	(0.083)	(0.190)	(0.153)	(0.151)
α_3 ACT Subsidy×Upper Tertile	0.130	-0.108	-0.035	0.176	-0.194*	0.019	0.068	0.004	-0.115
	(0.085)	(0.082)	(0.051)	(0.115)	(0.114)	(0.059)	(0.127)	(0.100)	(0.095)
P-value: $\alpha_1 = \alpha_2 = \alpha_3$	0.807	0.066*	0.090*	0.820	0.217	0.026**	0.619	0.281	0.897
DV Mean (Control Group)	0.494	0.290	0.216	0.438	0.375	0.188	0.585	0.154	0.262
N	2042	2042	2042	1332	1332	1332	705	705	705

Notes: The unit of observation is the first illness episode that the household experienced following the baseline. A few households have multiple observations if multiple household members were ill simultaneously. Standard errors clustered at the household level in parentheses. Standard errors for Specification 2 are bootstrapped with 500 replications. All regressions control for household head age, RDT treatment status, and a full set of strata dummies. Literacy status is missing for 5 households. Tertile cutoffs are illustrated in Figure 5. The distribution of first episodes between tertiles 1, 2, and 3 is 27.1, 35.5, and 37.4 percent for literate households and 45.3, 28.9, and 25.8 percent for illiterate households. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 3. Impact of ACT Subsidy on ACT Access by Literacy and Predicted Malaria Positivity

	Illness Treated with ACT		
	All	Literate	Illiterate
Specification 1 - Main Effect			
α ACT Subsidy	0.153***	0.081	0.272***
	(0.041)	(0.057)	(0.056)
Specification 2 - Impact by Predicted Malaria Positivity			
α_1 ACT Subsidy×Lower Tertile	0.187***	0.167	0.225***
	(0.074)	(0.114)	(0.085)
α_2 ACT Subsidy×Middle Tertile	0.132	0.056	0.292**
	(0.089)	(0.113)	(0.140)
α_3 ACT Subsidy×Upper Tertile	0.146*	0.057	0.289***
	(0.086)	(0.106)	(0.118)
P-value: $\alpha_1 = \alpha_2 = \alpha_3$	0.881	0.730	0.864
DV Mean (Control Group)	0.259	0.365	0.108
N	2042	1332	705

Notes: See Table 2 notes.

Table 4. Impact of Lowering ACT Subsidy Level on ACT Access and Targeting

	(1)	(2)	(3)	(4)	(5)
Panel A. Retail-Sector ACTs					
	Redeemed First ACT Voucher	Redeemed First ACT Voucher for Child (Ages 13 and Below)	Redeemed First ACT Voucher for Adult (Ages 14 and Above)	First ACT Voucher was Redeemed for Malaria Positive Patient (RDT Result)	Predicted Malaria Positivity of Patient for Whom First ACT Voucher was Redeemed
α_1 ACT Subsidy = 88%	-0.026	0.033	-0.059**	0.187**	0.112***
	(0.038)	(0.034)	(0.027)	(0.080)	(0.042)
α_2 ACT Subsidy = 80%	-0.055	0.027	-0.082***	0.182**	0.107***
	(0.037)	(0.034)	(0.026)	(0.084)	(0.043)
α_3 ACT Subsidy = 0%	-0.384***	-0.209***	-0.175***		
	(0.032)	(0.029)	(0.021)		
P-value: $\alpha_1 = \alpha_2 = 0$	0.336	0.592	0.006***	0.036**	0.011**
DV Mean (ACT 92%, no RDT)	0.439	0.268	0.171	0.563	0.424
N	2789	2789	2789	687	685
Panel B. Overall ACT Access					
	Ilness Treated With ACT	*If Child (Ages 13 and Below):* Illness Treated With ACT	*If Adult (Ages 14 and Above):* Illness Treated With ACT		*If Illness was Treated With ACT:* Predicted Malaria Positivity
α_1 ACT Subsidy = 88%	-0.044	0.002	-0.135		0.090*
	(0.060)	(0.081)	(0.086)		(0.051)
α_2 ACT Subsidy = 80%	-0.019	0.023	-0.094		0.042
	(0.058)	(0.080)	(0.083)		(0.051)
α_3 ACT Subsidy = 0%	-0.174***	-0.099	-0.263***		0.053
	(0.056)	(0.080)	(0.076)		(0.057)
P-value: $\alpha_1 = \alpha_2 = 0$	0.758	0.948	0.285		0.213
DV Mean (ACT 92%, no RDT)	0.457	0.462	0.450		0.431
N	2042	1166	874		858

Notes: Panel A: The unit of observation is the household. The omitted category is the 92% ACT-only subsidy group. Panel B: The unit of observation is the first illness episode that the household experienced following the baseline. 14 is the cutoff age above which the "adult dosage" is recommended (see Figure A1). Robust standard errors clustered at the household level when applicable in parentheses. All regressions include an RDT dummy and its interactions with the ACT price dummies. Regressions in first three columns control for a full set of strata dummy variables. Regressions in columns 4 and 5 omit strata and age controls so as not to absorb selection effects, which these regressions aim at identifying. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 5. Estimated Impacts of Various Subsidy Schemes on Under- and Over-Treatment

	No Subsidy	ACT 92% Subsidy	ACT 80% Subsidy	ACT 80% + RDT Subsidy
Experimental Estimates of Access and Drug Shop Targeting				
Total Share Taking ACT	0.282	0.457	0.437	0.432
Share Taking ACT at Drug Shop	0.170	0.355	0.334	0.338
Share Taking ACT at Health Center	0.113	0.101	0.104	0.094
Targeting at Drug Shop	0.745	0.563	0.745	0.806
Assumptions for Estimates of Under- and Over-Treatment				
Share of illness episodes that are malaria [a]	0.386	0.386	0.386	0.386
Targeting at Health Center (Medium) [b]	0.75	0.75	0.75	0.75
Targeting at Health Center (High)	0.85	0.85	0.85	0.85
Targeting at Health Center (Low)	0.65	0.65	0.65	0.65
Under- and Over-Treatment: Preferred Estimates (assuming Medium Targeting at Health Center)				
Overall Targeting	0.747	0.605	0.747	0.794
Over-treatment	0.116	0.294	0.181	0.145
Under-treatment	0.453	0.284	0.153	0.110
Under- and Over-Treatment: Alternative Estimates (assuming High Targeting at Health Center)				
Overall Targeting	0.787	0.627	0.770	0.816
Over-treatment	0.098	0.277	0.164	0.130
Under-treatment	0.424	0.258	0.126	0.086
Under- and Over-Treatment: Alternative Estimates (assuming Low Targeting at Health Center)				
Overall Targeting	0.707	0.583	0.723	0.772
Over-treatment	0.135	0.310	0.197	0.160
Under-treatment	0.482	0.310	0.180	0.135

Notes: Targeting (T) is the share of ACTs taken for illness episodes that are malaria. Over-treatment (OT) is the share of non-malaria episodes treated with an ACT. Under-treatment (UT) is the share of malaria episodes not treated with an ACT. See section 3 (p. 9) for the formulas relating T, OT and UT to the estimated parameters.

[a] The assumption on the share of illness episodes that are malaria (Π) is based on the rate observed in the symptoms database collected through unannounced household visits during which rapid diagnostic tests for malaria were administered. See text on pp. 15-16 for details.

[b] We consider three possible levels of targeting at health centers since there is no clear evidence from the literature on this parameter.

Table 6. External Validity Comparisons

	Central Uganda[a]	Eastern Uganda[b]	Western and Southeastern Tanzania[c]	Southern Malawi[d]
	November-December 2010	May-June 2011	March 2011	January-March 2011
Malaria Burden (reported/perceived)				
HH Had at least one (Presumed) Malaria Episode (Past Month)	0.590	0.354	0.273	0.410
Treatment Seeking for Malaria				
Public Sector	0.250	0.333	0.417	0.760
Private Sector*	0.660	0.426	0.392	0.120
No Treatment Sought	0.090	0.221	0.187	0.120
Malaria Diagnosis (Any Blood Malaria Test)				
Last Month	0.150	0.225		
Last Suspected Episode			0.360	
Current Illness Episode				
Medication Taken				
Took ACT (Suspected Malaria)	0.330	0.376	0.496	
Took ACT (Sought Treatment)				
Antimalarial Cost	1.690	1.355	1.366	
Malaria Positivity Among The General Population				
Under 5		0.512		
Ages 5 - 13		0.644		
Ages 14 and Up		0.351		
Malaria Positivity Among Drug Shop Patients Buying Subsidized ACTs				
Under 5	0.740			
Ages 5 - 13	0.780			
Ages 14 and Up	0.470			

*Includes private clinics and retail sector

[a]Survey conducted in Luwero district. Malaria positivity figures are among purchasers of subsidized ACTs sold over-the-counter in local drug shops, with price ranging from $0.10 - $0.40 by age group/dosing level. Funding: Department for International Development, Clinton Health Access Initiative and Bill and Melinda Gates Foundation. Author: Jessica Cohen

[b]Survey conducted in Budaka, Bukedea, Kibuku, Kumi, Ngora and Pallisa districts. Malaria positivity figures are among household members from a random sample of the population. Funding: Clinton Health Access Initiative and Bill and Melinda Gates Foundation. Authors: Jessica Cohen, William Dickens, Gunther Fink

[c]Survey conducted in Mtwara and Rukwa regions. Funding: Clinton Health Access Initiative and Bill and Melinda Gates Foundation. Authors: Jean Arkedis, Jessica Cohen, Julius Massaga, Prashant Yadav

[d]Survey conducted in Machinga and Balaka districts. Funding: Bill and Melina Gates Foundation. Authors: Pascaline Dupas, Dean Karlan, Jonathan Robinson

Appendix Figure A1. ACT Price and Dosing Guide

	Recommended Dose and Corresponding Dose Cost for:			
	Adult (14+)	**Ages 9-13**	**Ages 4-8**	**Ages 3m-3y**
Dose Price Per Pill	4 pills, twice a day for three days	3 pills, twice a day for three days	2 pills, twice a day for three days	1 pill, twice a day for three days
Ksh 20.83 (Control)	Ksh 500	Ksh 375	Ksh 250	Ksh 125
Ksh 4.16 (80% Subsidy)	Ksh 100	Ksh 75	Ksh 50	Ksh 25
Ksh 2.50 (88% Subsidy)	Ksh 60	Ksh 45	Ksh 30	Ksh 15
Ksh 1.66 (92% Subsidy)	Ksh 40	Ksh 30	Ksh 20	Ksh 10

Notes: The exchange rate at the time of the study was around 78 Ksh to US$1. The tables reads as follows. Column 1: The unsubsidized ACT cost is KSh500 ($6.25) for an adult dose (age 14+). 80%, 88% and 92% subsidies correspond to KSh100 ($1.25), KSh60 ($0.75) and KSh40 ($0.50) for an adult dose, respectively.

Ideal dosing is based on weight but manufacturers and the Kenyan Ministry of Health provide age guidelines as well, as it is not always feasible to weigh malaria patients. This study used the age guidelines from the Kenya Ministry of Health.

Appendix Table A1. Baseline Treatment Seeking Behavior

		By Household SES			By Patient's Age		
	All	Literate	Illiterate	P-value Lit.=Illit.	Patient 13 or Younger	Patient 14 or Older	P-value Child= Adult
Household Level Malaria and Diagnostic Incidence							
Number of Presumed Malaria Episodes Last Month	1.22	1.36	0.994	0.000***	0.617	0.568	--
At Least One Presumed Malaria Episode Last Month	0.685	0.739	0.600	0.000***	0.435	0.387	--
HH Member Took RDT Test in Last Month (if Reported Malaria)	0.040	0.041	0.038	0.732	--	--	--
HH Member Took Microscopy Test in Last Month (if Reported Malaria)	0.251	0.275	0.202	0.000***	--	--	--
Treatment Seeking for All Presumed Malaria Episodes							
Did not Seek Care	0.182	0.260	0.147	0.000***	0.139	0.218	0.000***
Went to Health Center	0.413	0.331	0.448	0.000***	0.470	0.364	0.000***
Went to Drug Shop	0.369	0.354	0.376	0.337	0.357	0.382	0.159
Medication for All Presumed Malaria Episodes							
No Antimalarial Taken	0.221	0.302	0.186	0.000***	0.184	0.252	0.000***
Took ACT	0.213	0.120	0.255	0.000***	0.240	0.193	0.002***
Took Sulfadoxine-Pyrimethamine (SP)	0.100	0.074	0.112	0.004***	0.075	0.130	0.000***
Took Amodiaquine (AQ)	0.181	0.166	0.187	0.240	0.212	0.153	0.000***
Took Other Antimalarial	0.072	0.055	0.079	0.029**	0.095	0.050	0.000***
Forgot Name of Antimalarial Taken	0.217	0.285	0.185	0.000***	0.198	0.225	0.089*
Source of Antimalarials (Among Antimalarial Takers)							
Health Center	0.444	0.413	0.454	0.130	0.475	0.416	0.005***
Drug Shop	0.523	0.540	0.518	0.437	0.498	0.552	0.011**
Another Source	0.033	0.048	0.028	0.069*	0.027	0.032	0.414
Cost per Episode (Among Antimalarial Takers)							
Total Cost ($US)	1.68	1.38	1.80	0.014**	1.44	1.97	0.000***

Notes: Standard errors clustered at household level for episode-level statistics. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively. 14 is the cutoff age above which the "adult dosage" is recommended (see Figure A1).

Appendix Table A2. Reporting Bias With Endline Illness Episodes

	Reported Any Illness Episode	Number Episodes Reported	Predicted Malaria Positivity - First Episode	Days Ago - First Episode	Patient Age - First Episode
A. All Households					
ACT 92%	0.015	0.024	0.013	1.73	-1.71
	(0.020)	(0.157)	(0.025)	(3.86)	(1.65)
ACT 88%	0.002	-0.063	0.028	4.72	-2.92*
	(0.021)	(0.155)	(0.025)	(3.75)	(1.61)
ACT 80%	-0.020	-0.168	0.010	3.19	-1.69
	(0.021)	(0.155)	(0.025)	(3.78)	(1.62)
Any RDT	0.006	-0.025	0.004	-1.27	0.906
	(0.010)	(0.078)	(0.012)	(1.87)	(0.777)
Surprise RDT Test	0.001	0.089	-0.021*	5.09***	0.988
	(0.010)	(0.079)	(0.012)	(1.95)	(0.797)
P-value (92=88=80)	0.005***	0.101	0.315	0.388	0.221
DV Mean	0.950	3.05	0.411	64.7	19.1
N	2621	2621	2473	2438	2473
B. Literate Headed Households					
ACT 92%	0.014	0.389	0.032	5.29	-3.88
	(0.034)	(0.242)	(0.041)	(5.77)	(3.19)
ACT 88%	-0.012	0.178	0.030	4.88	-5.48*
	(0.034)	(0.232)	(0.041)	(5.61)	(3.15)
ACT 80%	-0.044	0.032	0.003	3.99	-2.89
	(0.034)	(0.237)	(0.040)	(5.64)	(3.11)
Any RDT	0.010	-0.240*	-0.034*	-6.95**	4.00***
	(0.018)	(0.133)	(0.021)	(3.09)	(1.66)
Surprise RDT Test	-0.006	0.211	-0.031	11.7***	1.24
	(0.020)	(0.131)	(0.021)	(3.17)	(1.70)
P-value (92=88=80)	0.025**	0.076*	0.333	0.933	0.302
DV Mean	0.932	2.76	0.350	59.5	26.8
N	1023	1023	861	843	861
C. Illiterate Headed Households					
ACT 92%	0.020	-0.163	0.009	1.05	-0.887
	(0.026)	(0.209)	(0.032)	(5.26)	(1.84)
ACT 88%	0.013	-0.201	0.028	4.92	-1.61
	(0.027)	(0.210)	(0.032)	(5.12)	(1.80)
ACT 80%	-0.005	-0.296	0.015	2.96	-1.05
	(0.027)	(0.208)	(0.032)	(5.20)	(1.83)
Any RDT	0.003	0.107	0.024*	1.03	-0.746
	(0.010)	(0.097)	(0.014)	(2.35)	(0.806)
Surprise RDT Test	0.007	0.003	-0.017	1.42	0.948
	(0.011)	(0.100)	(0.015)	(2.44)	(0.819)
P-value (92=88=80)	0.091*	0.465	0.479	0.365	0.688
DV Mean	0.962	3.23	0.444	67.5	15.0
N	1591	1591	1606	1589	1606

Notes: Robust standard errors (clustered at the household level when relevant) in parentheses. All regressions include full set of strata dummies and a control for household head age. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Appendix Table A3. Predicting Malaria Positivity - Probit Marginal Effects

	Coefficient	Standard Error
Cough	-0.001	(0.061)
Chills	0.132	(0.097)
Headache	0.125*	(0.072)
Diarrhea	0.247***	(0.084)
Runny Nose	-0.119**	(0.060)
Vomiting	0.063	(0.072)
Body Pain	0.197*	(0.111)
Malaise	-0.052	(0.149)
Poor Appetite	0.131	(0.104)
Age 14 or Above	0.398*	(0.239)
Age	0.106***	(0.032)
Age Squared	-0.008***	(0.003)
(Age 14 or Above)×Cough	-0.096	(0.126)
(Age 14 or Above)×Chills	-0.235**	(0.113)
(Age 14 or Above)×Headache	-0.070	(0.126)
(Age 14 or Above)×Diarrhea	-0.221*	(0.131)
(Age 14 or Above)×Runny Nose	0.222	(0.147)
(Age 14 or Above)×Vomiting	0.089	(0.155)
(Age 14 or Above)×Body Pain	-0.106	(0.133)
(Age 14 or Above)×Malaise	-0.075	(0.171)
(Age 14 or Above)×Poor Appetite	0.005	(0.260)
(Age 14 or Above)×Age	-0.138***	(0.034)
(Age 14 or Above)×Age Squared	0.009***	(0.003)
DV Mean / N	0.003	1386

Notes: Standard errors in parentheses. Data source: Symptoms database (see text sections 4.3 and 4.4 for details). ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively. We do not include the most commonly cited symptom of malaria, fever, in order to avoid endline reporting bias. In Kiswahili, the word for "fever" (*homa*) is commonly used to refer to "malaria". A concern is that if the subsidy regimes we study affected the likelihood that people get a formal diagnosis, this would make the reporting of *homa* endogenous. The pseudo R^2 on the probit declines from 0.2191 to 0.2103 when excluding fever and its interaction with the age variables. In practice, our results are very similar when including fever in prediciting malaria positivity (though including fever does appear to introduce some reporting bias).

Appendix Table A4. RDT Take-Up by RDT Price

	Took RDT	Sought Treatment at Drug Shop	Took RDT | Sought Treatment
Free RDT	0.354***	0.016	0.812***
	(0.023)	(0.029)	(0.028)
RDT sold at Ksh 15, bundled refund[a]	0.362***	0.055*	0.767***
	(0.023)	(0.029)	(0.030)
RDT sold at Ksh 15, no refund	0.342***	0.020	0.780***
	(0.019)	(0.025)	(0.025)
P-value (equality of RDT treatments)	{0.787}	{0.419}	{0.462}
Any RDT	0.351***	0.029	0.784***
	(0.013)	(0.021)	(0.018)
DV Mean (No RDT)	0.005	0.415	0.012
N	2609	2609	1131

Notes: All results make use of administrative drug shop data. Sample restricted to households selected for subsidized ACTs. Heteroskedasticity robust standard errors in parentheses, standard deviations in brackets, p-values in braces. All regressions include controls for ACT price treatment, surprise RDT selection, and a full set of strata dummies. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

[a] Households in the "bundled refund" group received a refund for the RDT cost in the form of a Ksh15 rebate on the ACT price if the RDT test was positive.

Appendix Table A5. RDT Take-Up by RDT Exposure

	(1)	(2)
	Redeemed RDT Voucher at Subsequent Visit | Sought Treatment Once	Redeemed RDT Voucher (Any Visit)
Panel A. Learning from Own Experience		
(Randomly) Selected for Surprise RDT at First Drug Shop Visit	0.100**	0.022
	(0.044)	(0.022)
Panel B. Learning from Neighbors		
Share Neighbors (Within 750m radius) Randomly Selected for RDT Voucher or Surprise RDT		1.06***
		(0.308)
DV Mean	0.376	0.387
N	723	1619

Notes: Both samples restricted to households selected for an RDT subsidy. Column 1 further restricts sample to households that visited the drug shop at the first illness. All regressions include controls for ACT treatment, strata fixed effects, and dummies for whether respondent has heard of ACTs, heard of RDTs, and named ACTs as the best antimalarial at baseline. The learning from neighbors regressions also include controls for the share of neighbors selected for each ACT treatment, and the total number of neighbors in a 750m radius. Heteroskedasticity robust standard errors in column 1. Spatially clustered standard errors in column 2.