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

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Abstract

In response to parasite resistance to older malaria medicines, the global health community is planning to make new, more effective malaria treatments called Artemisinin Combination Therapies (ACTs) available over-the-counter at heavily subsidized rates throughout Africa. While this may go a long way toward reducing under-treatment (thereby saving lives in the short-run), it is also likely to increase over-treatment, wasting subsidy dollars and contributing to drug resistance (thereby making lives harder to save in the long-run). We use data from a randomized controlled trial conducted with over 2,700 households in rural Kenya to study behavioral responses to changes in ACT prices and quantify this tradeoff. We find that ACT use increases by 59 percent in the presence of an ACT subsidy over 90 percent. However, only 56 percent of those buying such a highly subsidized ACT at the drug shop test positive for malaria. We show that this share increases (without substantially compromising access) to 81 percent when the over-the-counter ACT subsidy is somewhat reduced and resources are redirected towards a subsidy for rapid malaria tests. Making such tests available over-the-counter more than doubles the rate at which illnesses are tested for malaria, confering benefits that extend beyond improved targeting of the ACT subsidy.

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1 Introduction

Limiting the spread of infectious disease 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 childhood 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 a trade-off 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 drug resistance has rendered all earlier generations of antimalarials (chloroquine, amodiaquine, sulfadoxine-pyrimethamine) largely ineffective. Due to continuing disease resistance concerns, the use of artemisinin derivatives by themselves as monotherapies is highly discouraged by the World Health Organization (WHO). Instead, the WHO encourages the use of ACTs, which combine an artemisinin derivative with a partner drug (such as mefloquine or lumefantrine), and thereby help protect the artemisinin derivatives from resistance.[1] Unfortunately, the unsubsidized price of ACTs ($6-8) is prohibitive for the great majority of households living in malarious regions and as a result, in 2008, 6 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

[1]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 combinations. When the combined drugs have differing modes of action, the probability of this event occurring is substantially lower than the probability of resistance developing to any single drug alone (World Health Organization 2010a).

Organization (2009)). In response, a call was made for a global ACT subsidy, to achieve two main goals: (1) immediately *save lives,* by increasing access to ACTs, 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 8 countries.

The AMFm subsidy was explicitly designed to reduce the price of ACTs in the retail sector, 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 quite likely that a substantial decrease in ACT prices will be associated with increases in not only appropriate but also inappropriate ACT use. A high rate of overtreatment with ACTs is problematic for several reasons. First, it is a waste of a vast amount of subsidy money. The co-payments alone for the AMFm are estimated to cost $216 million in the pilot phase (Global Fund to Fight AIDS, TB and Malaria 2010). Second, if the retail-sector 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). Finally, a high rate of overtreatment for malaria may contribute to the selection of drug resistant parasites (Perkins and Bell 2008; White 2004). This means that, although ACT subsidies would have a first order (positive) effect on resistance because of artemisinin monotherapy crowd-out, there could be a second order negative effect of accelerating resistance from overtreatment with ACTs.

One possible way to preserve ACT access while minimizing overtreatment is to jointly subsidize malaria diagnostic tests along with malaria treatment over-the-counter in drug shops. However, the attractiveness of this policy will depend on individuals' demand for and adherence to test results. We use data from a randomized controlled trial conducted with over 2,700 households in rural Kenya to: (1) study the tradeoffs between ACT affordability and overuse in the context of the AMFm subsidy and (2) test an alternative to the AMFm subsidy regime that addresses the problem of overuse by providing access to a subsidized rapid diagnostic test for malaria (RDT) in tandem with subsidized ACTs.[2]

We show that subsidies for ACTs and RDTs can successfully broaden access to these tech-

[2]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 antibodies can be determined within approximately 15 minutes. Non-clinical staff can easily learn to perform the test and interpret the results.

nologies, and that including RDT subsidies in an ACT subsidy policy could be an effective way to improve the targeting of subsidized ACTs to people with confirmed malaria. We also show that this RDT subsidy could be cost-effectively financed by reducing the ACT subsidy somewhat, especially since modest decreases in the ACT subsidy improve the targeting of ACTs to those most likely to have malaria without meaningfully reducing ACT access. This is primarily due to two stark results from our experiment:

1. Over-treatment of malaria is extremely common in our study context, particularly among teenagers and adults (see Figure 1). As a result, when ACTs are heavily subsidized, only 38 percent of adults who seek treatment for malaria at the drug shop actually have malaria. This implies that improving diagnostic access has the potential to considerably reduce over-treatment.

2. The demand for ACTs is relatively inelastic at low prices, even among the poorest households (see Figure 2). Specifically, we see a modest 13 percent decline in ACT purchases at the drug shop when the retail price subsidy declines from 92 to 80 percent, corresponding to a 150 percent price increase. For children, who are much more likely to actually have malaria and for whom malaria is most dangerous, there is no significant price sensitivity in this range. This implies that some reduction in the ACT subsidy (compared to the current AMFm target) is unlikely to meaningfully reduce access among those most likely to have malaria, while it can help screen out those less likely to have malaria (adults).

In order for the 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 get the patient tested with 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 ever 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 the ACT.[3] This behavior likely reflects 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 tend to ignore test results and prescribe antimalarials to those who test negative. Individuals may still value taking the test, even

[3]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.

though they don't adhere to the results, because the test result provides an indicator as to whether or not additional medication should be taken, or because this helps them learn about the efficacy of ACTs and RDTs. Indeed, 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.

Overall, our estimates suggest that moving from a policy regime with ACT subsidies only to one that 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 than the one proposed by the AMFm 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. However, the ACT subsidy disproportionately increases access among illiterate headed households, nearly closing the gap in ACT use between literate and illiterate households. The slightly lower ACT subsidy would also primarily benefit children, who are much more susceptible to malaria than adults. In fact, for children, the benefit of adding an RDT subsidy to the ACT subsidy would not be in averting over-treatment, but rather in ensuring that in those cases where a child suspected of having malaria does not actually have malaria, the true illness is diagnosed and treated faster.

Beyond its immediate relevance to the AMFm subsidy initiative, 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 on underdiagnosis and overtreatment, 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 Cameroun, 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 overuse is not a problem, and for which the objective of the social planner is to expand access while limiting *underuse* among subsidy beneficiaries.[4] In contrast, this paper considers the price-setting problem that arises when overuse generates negative externalities (in our case, through drug resistance). While earlier evidence (from the same part of Kenya) showed that cost-sharing did not improve targeting of malaria prevention subsidies (Cohen and Dupas 2010; Dupas 2010), here we find evidence that higher rates of cost-sharing can improve targeting of malaria treatment subsidies. The targeting effect we find here could be somewhat "mechanical", however. A higher price-per-pill increases the price tag substantially more (in absolute terms) for adults (who require a higher dosage) than for children. Therefore proportional price increases (such as the ones we study) could result in a greater decrease in demand among adults even if households are unaware of the malaria risk ratio between adults and children, and do not value treating children more than adults.

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 trade-offs inherent in heavily subsidizing ACTs. Section 4 describes our experimental design and data. We discuss the results in Section 5 and perform a cost-effectiveness analysis in Section 6, before we conclude in Section 7.

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

2 Background

2.1 Background on Malaria

Malaria is a disease caused not by "bad air", as was once believed, but by a blood parasite called *Plasmodium*, which is transmitted from human to human by female anopheles mosquitoes. 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 under the age of five (World Health Organization 2009).

Despite major strides in malaria eradication in the early and mid-20th century, notably in the Americas (Bleakley 2010; Lucas 2010), efforts to eradicate malaria worldwide were abandoned in the 1970s. Recently, efforts to control malaria transmission have rejuvenated with the introduction of highly effective prevention tools, such as long-lasting insecticide treated bednets. These nets have been distributed on a massive scale in the past five years, contributing to reductions in malaria incidence and deaths in some countries (Otten et al. 2009). The morbidity burden of malaria remains considerable, however, and there is no malaria vaccine on the near horizon. Given this, policy-makers and donors have recently been turning their attention to malaria treatment, an aspect of malaria control where less progress has been made.

Because immunity to malaria develops with repeated exposure, children under 5 are most vulnerable to acquiring and dying from malaria. 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, the vast majority of children under the age of 5 with presumed malaria are not treated with effective antimalarial drugs, but are rather treated with older antimalarials to which the parasite has gained resistance.

Cost is a major driver of this access gap. Currently, the only effective antimalarial against the *P. falciparum* parasite is artemisinin, a compound derived from Chinese wormwood trees that is significantly more expensive to produce than older, synthetic forms of malaria medicine. Artemisinin acts quickly to bring down the parasite load (patients often feel significantly better within 24 hours) and has only mild side effects. The retail price of artemisinin-based antimalarials is roughly $6-8 in Sub-Saharan Africa.[5] In most populations dealing with endemic malaria this cost of treatment is unaffordable.

[5]ACT Watch, Population Services International, Outlet Surveys (http://www.actwatch.info). The median price of Artemether Lumefantrine (the drug used in this study) in drug shops is $5.26 in Uganda, $6.03 in Benin, $4.58 in DRC, $5.36 in Nigeria and $5.36 in Zambia. In most cases, other ACTs are $1 more expensive, and all ACTs are more expensive in pharmacies than in drug shops.

2.2 Malaria Treatment Seeking in Rural Kenya

In Kenya, as in many developing countries, people can choose to treat malaria in a vast array of public, private and retail venues. Because the private health facilities are quite expensive and high-level public health facilities are generally in district centers and urban areas, the rural poor tend to seek malaria treatment either in lower-level health facilities ("clinics" and "dispensaries") or in drug shops.[6] Lower-level health facilities are typically staffed with nurses or medical assistants and are known to have high rates of absenteeism and stock outs of essential medicines, including ACTs (Kangwana et al. 2009; Chaudhury et al. 2006). 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, diagnosis, etc. (as is often the case in our study area) and if it takes a long time to reach the facility and be seen by a medical professional.

Rural health facilities generally do not have rapid diagnostic tests (RDTs), but often do blood slide microscopy tests for malaria, though this depends on the availability of a trained lab technician and stocks of slides and reagents. The quality of microscopic diagnosis of malaria can vary greatly with the experience and training of the lab technician and with the quality of the equipment. Given this, microscopy has a large rate of false negatives when used by health workers in the field: 31 percent, according to a 2002 study in Kenya (Zurovac et al. 2006). Compliance with test results is, in turn, quite low, even among health practitioners.[7] For example, the Kenya study cited above found that nearly 80 percent of patients who tested negative for malaria were still prescribed antimalarials. Overprescription rates had decreased somewhat by 2010, but remained as high as 50 percent among those above the age of 5, despite the introduction of strict guidelines for health workers to test and adhere to test results for patients above 5 (Juma and Zurovac 2011).[8]

Households also often treat illnesses with over-the-counter medication purchased at drug shops. 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). The two main benefits to treating an illness at a drug shop, rather than a public health facility, are convenience and choice. Drug shops are ubiquitous in Kenya, even in the most

[6] At endline, just 4 percent of all illness episodes in our study households were treated in the formal private sector.

[7] The reasons why negative malaria tests are so often ignored by medical practitioners in Africa is the subject of a growing body of public health research. Some explanations include historical presumptive treatment of malaria, risk aversion, lack of confidence in the test results, professional norms and patient demands (Chandler et al. 2008).

[8] In populations with high parasite density, properly manufactured RDTs can have a lower rate of false negatives than microscopy: generally under 5 percent in lab settings (World Health Organization 2010b) and around 8 percent in the field. (de Oliveira et al. 2009).

remote areas, and as a result most households live within 2 kilometers from such a shop. (In contrast, the average household in our sample lives 6.6 kilometers away, as the crow flies, from the nearest health facility). These shops are also often open reliably and offer a wide variety of medications to treat malaria (for example, many of the shops we visited during our pilot phase were open 12 hours a day, 6-7 days of the week). Drawbacks to treating malaria at a drug shop rather than a public health facility include the lack of diagnostic capability, the risk of receiving lower quality or counterfeit drugs, and of course the absence of emergency medicines and equipment to treat severe malaria infections. Perhaps the primary drawback is that unsubsidized ACTs are prohibitively expensive at retail outlets while, though often stocked out, they are in principle free in public facilities for those diagnosed with malaria.

Treatment seeking for malaria in our study population reflects these more general patterns in Africa overall. In a baseline survey conducted with female household heads, we asked detailed questions about how they treated perceived malaria episodes. (These baseline results on treatment seeking can be found in Appendix Table A1. We will discuss in detail how the sample was formed and how the data was collected in Section 4.) Overall presumed malaria incidence in Western Kenya is very high, with nearly 70 percent of households reporting a recent episode of malaria.[9] Most households either go to the health facility (41 percent) or to the drug shop (37 percent) to treat malaria, though a substantial minority (18 percent) does not seek care at all. Most of these episodes are undiagnosed, with 18 percent and 3 percent of households receiving a microscopy test or RDT respectively. The drug shop is the most common source of antimalarial medication and households spend on average $1.68 per malaria episode, a remarkably large sum of money given that the agricultural daily wage in this area is around $1.50 (Dupas and Robinson 2011). Only 21 percent of presumed malaria episodes were reported to be treated with ACTs, a rate that was not much higher for children, while roughly 35 percent of malaria episodes were treated with older, less effective medications.

2.3 The Affordable Medicines Facility for Malaria (AMFm)

The Affordable Medicines Facility for malaria (AMFm) is a policy response to these low rates of ACT access in malaria-endemic areas, funded by the Gates Foundation, UNICEF and others and hosted by the Global Fund. Through a co-payment to ACT manufacturers (a "global subsidy"), the program aims to reduce the price of ACTs by roughly 95 percent to

[9]Somewhat surprisingly, literare households report a higher malaria incidence than illiterate households. This might come from the fact that recall bias varies with socio-economic status. Using Indian data, Das et al. (2011) show that differential recall effects across income groups can reverse the sign of the gradient between doctor visits and per-capita expenditures.

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 unrestricted, but the aim is for retail sector ACTs to be cheap enough for most rural, poor populations to afford them, to be competitive with older, less effective antimalarials like amodiaquine, and to crowd out artemisinin monotherapy altogether. For example, the Kenyan government has set a "target" maximum retail price for ACTs purchased under the AMFm of Ksh 40 ($0.50). This price corresponds to the upper end of the AMFm's $0.20-$0.50 expected retail price range (Roll Back Malaria AMFm Task Force 2007).[10] The AMFm launched in early 2011 as a pilot in 8 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 highlight the access-overtreatment trade-off inherent to the AMFm approach of subsidizing ACTs through the retail sector. The trade-off is embedded in the following two policy parameters of interest:

- The share of true malaria episodes that do not get treated with ACTs; we denote this as "UT" for "under-treatment".
- 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, since overtreatment has the negative social externalities we discussed earlier (parasite resistance and wasted public resources). 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 $f(UT, OT)$), subject to a budget constraint. To stay as general as possible, we avoid imposing a specific functional form for the social planner's objective's function.

[10] It should be noted that a price of Ksh 40 corresponds to a 92 percent reduction in ACT retail prices in our study area (i.e. a 95 percent subsidy at the top of the supply chain moves down the chain more or less proportionally). In production theory, it is not standard that cost subsidies are passed down the supply chain in this manner. However, a supply side analysis is outside the scope of this paper. We take the AMFm target prices as given, and study consumer demand assuming that these targets can be achieved.

Another parameter of interest, which will feature prominently in our empricial analysis, is the fraction of ACT takers who are malaria positive, which we denote by T for "targeting". Let Π represent the fraction of all illness episodes that are actually malaria. Then we can express T as follows:

$$T = \frac{(1 - UT)\,\Pi}{(1 - UT)\,\Pi + OT\,(1 - \Pi)}$$

In a first-best world, decreasing UT while keeping OT at a minimum could be easily achieved by simply making the ACT subsidy conditional: only those with a positive malaria test result would be allowed to buy an ACT at the subsidized price. This is the idea behind the Kenyan policy (started approximately one year prior to our study) of free ACT distribution to those diagnosed with malaria at health centers. It is clear from our baseline data that access to health centers is limited, however; hence the AMFm plan to roll out a subsidy that impacts the retail sector.[11]The remainder of this section discusses how such a proposed subsidy will affect UT, OT, and T.

3.1 Model Setup

We consider an environment where, when faced with an illness shock, the household has three possible actions, a:

1. Buy ACTs at the drug shop: $a = s$.
2. Seek diagnosis at a formal health facility and receive ACTs if positive: $a = h$.[12]
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. The expected value of taking a particular action $a \in \{s, h, n\}$ depends on this probability, and is denoted by

[11]Unfortunately, enforcing a first-best conditional subsidy policy in the retail sector is not particularly feasible. Absent vigilant monitoring and sanctioning (which is not available in the Kenyan, and most other, developing country contexts), profit-maximizing drug shops would not have any incentive to adhere to the conditionality.

[12]Given that health providers often prescribe ACTs to individuals with negative malaria test results, we will discuss the impacts of loosening this assumption in subsection 3.4

$V^a(\pi)$. 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.[13] 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 that $V^a(\pi) - V^n(\pi)$ increases with π for $a \in \{s, h\}$ (we refer to this as assumption A1). 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, there may be heterogeneity in these valuations in the population. For example, the relative cost (in utility terms) of higher priced ACT medication will be lower for wealthier households. In order to study heterogeneity and to 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 travelling to the health center at higher malaria probabilities (i.e. when people are most certain it is malaria). We consider this to be the most plausible scenario, but other configurations are certainly possible. Under such a scenario, "rich" households with a malaria probability above π_2 elect to purchase an ACT from

[13] We assume that $V^a : \pi \to \mathbb{R}$ is a function, not a correspondence. This 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. However, restricting V^a to be a function simplifies our analysis and still provides useful guidance for the empirical work.

the drug shop. Those with a malaria probabiliy 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 chosing 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 chose to do nothing or to buy something else from the drug shop, no matter what their malaria probability is.

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 the health center price 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 *strictly* increase (unless $V^s(\pi)$ is everywhere dominated by either $V^h(\pi)$ or $V^n(\pi)$, even after the price reduction).

The following proposition formalizes the impact of the subsidy on the policy parameters of interest, assuming a homogeneous population:

Proposition 1 *Consider a population with identical value curves. An ACT subsidy at the drug shop leads to a decrease in UT, an increase in OT, and, provided T is defined prior to the subsidy, a decrease in T.*

Proof. Crowd out can occur from either the health center or from doing nothing/something else. First consider crowd-out from the health center. Since we have assumed that all cases at the health center are diagnosed and only given an ACT if the patient tests malaria positive, this crowd-out will leave UT unchanged and increase OT. This shift will clearly work to decrease T, provided T is defined prior to the subsidy.

Now consider crowd out from doing nothing/something else. This crowd out increases the number of illnesses treated with ACTs, but all these illnesses are treated presumptively, so both true and false malaria episodes are more likely to be treated with an ACT. That is, UT decreases and OT increases. By assumption A1, all the marginal illnesses that are treated under the subsidy regime (people induced to take action s instead of n by the subsidy) will have lower malaria probabilities than those illnesses that would have received ACTs anyway. This implies that T will decrease, provided it was defined prior to the subsidy. Note that

if no illnesses are treated with ACTs prior to the subsidy, both OT and UT will strictly increase (or remain unchanged if no illnesses are treated after the subsidy as well), but since T is undefined, we cannot make a statement about its directional change. ■

Proposition 1 thus states that for a population with uniform value curves, an ACT subsidy in the retail sector will increase access, but also increase overtreatment such that targeting gets unambiguously worse. However, when there is heterogeneity in valuations in the population, an ACT subsidy need not worsen targeting. 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 particularly important to pay attention to distributional impacts of the ACT subsidy. In particular, the subsidy would be especially attractive if it increased takeup 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. In this case the policy would be mostly wasteful.

3.3 Impact of Adding an RDT Subsidy at the Drug Shop

Suppose that at some cost, an individual can take a rapid diagnostic test for malaria at the drug shop. He or she must pay this cost with certainty. We assume that the diagnostics are perfectly accurate and that all individuals believe that this is the case. In this case, no one will ever take an antimalarial if they test negative. Then 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 diagnostic is less than the price of an antimalarial.

2. If the test is negative, it can help the individual to select medication appropriate for the true cause of the illness earlier

These effects imply that, conditional on not having malaria, the value of seeking care at the drug shop *and* seeing the negative RDT test result is greater than the value of seeking care

at the drug shop without seeing a test result. This brings us to our second main result:

Proposition 2 *Adding an RDT subsidy onto the ACT subsidy will decrease UT and decrease OT, compared to the ACT subsidy regime only. T will therefore increase.*

Proof. We consider the intensive and the extensive margin effects of RDTs in turn. Let's begin with the intensive margin effect: this applies to individuals for whom purchasing an ACT at the drug shop is optimal even 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. If individuals always comply with RDT results, this will leave UT unchanged while decreasing OT, which increases T.

Now consider the extensive margin. There may be a set of individuals for whom purchasing an ACT at the drug shop is not optimal in the absence of an RDT subsidy but becomes so once the RDT subsidy is introduced. When this extensive margin crowd out is from the health center, it will not contribute to changes in UT and OT, since patients will make the same medication choice at the drug shop as they would have at the health center: the choice that complies with the diagnostic test result. When this crowd out is from doing nothing/taking something else, it will work to decrease UT but leave OT unchanged, which increases T. ■

3.4 Allowing for Imperfect Compliance with Malaria Test Results

The discussion above assumes perfect compliance with test results at both the health center and the drug shop. Suppose compliance with the test result at the health center is partial, so some individuals who test malaria negative are still given ACTs. Proposition 1 will go through, since health center crowd out still increases OT while leaving UT unchanged. Now consider partial compliance with the RDT result at the drug shop. The intensive margin RDT effect will still increase T by decreasing OT (assuming that at least some individuals comply with the test result). However, the impact of the extensive margin effect is now ambiguous, since both UT and OT could increase, with the final impact on T being determined by the nature of crowd out and the degree of test compliance. We also note that if health centers do not always prescribe ACTs to malaria positive individuals, then Proposition 1 would no longer hold. If ACT access at the health center were very poor then the subsidy could actually increase targeting if individuals with the highest malaria probabilities were crowded out of the health center and into the drug shop by the subsidy policy.

3.5 Summary of Theory

The central takeaway of the above analysis is that the impacts of ACT and RDT subsidies on ACT targeting and crowd out are theoretically ambiguous. The impacts depend on unknown empirical objects, including 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"), the distribution of malaria positivity in the population, and compliance with test results. In what follows, we describe our field experiment, which we designed in order to learn about these objects and, with them, estimate the impacts of various policy regimes on access and targeting. Specifically, we introduced exogenous variation in the ACT subsidy level and in access to RDTs. We can then observe how crowd out in terms of treatment channel and therapy choice varies with malaria positivity. We also observe how the effects of the subsidies vary by socioeconomic status to assess the distributional impacts of the subsidy.

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.[14] 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. This region is rural and poor, with the majority of household heads working as subsistence farmers.

We selected four drug shops, in four rural market centers.[15] We then sampled all households in the catchment area (within a 4km radius) of each of these four drug shops. The total number of sampled households was 2,928. We then visited each household to administer a baseline survey to the female head of household, at the end of which two vouchers for ACTs and (when applicable) two vouchers for RDTs were distributed.[16] Enumerators explained that ACTs are the most effective type of antimalarial and, if the household received an RDT voucher, what the RDT was for and how it worked.[17] The vouchers stated the drug shop at

[14]The study protocol was approved by the UCLA IRB, the KEMRI/Kenya National Ethical Review Committee, the Kenya Pharmacy and Poisons Board, and the IPA Kenya IRB.

[15]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.

[16]In rare cases when there was no female head or she was not available, we interviewed the male head of household.

[17]The ACT used in this study was Coartem (Artemether Lumefantrine), produced by Novartis Pharma-

which the products could be purchased and did not have expiration dates so that households had no reason to redeem them 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 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.[18] 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, $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 less of the AMFm subsidy were passed through the supply chain, or if the subsidy amount were reduced, potentially to fund RDTs.[19] The third group received vouchers for both subsidized ACTs and RDTs, with households also randomized into one of three ACT subsidy levels and three RDT subsidy levels. The most expensive RDTs were subsidized by 85 percent, corresponding to a retail price of roughly $0.20.[20]

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 demonstrates the pricing and dosing regimens in the study.[21] The randomization of households was done using a computerized random number assignment algorithm and was stratified by drug shop, by the household's

ceuticals. 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).

[18]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.

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

[20]Some households received RDTs for free, some received RDTs subsidized at 85 percent, and some were offered a refund for the 85 percent subsidized RDT if they tested positive. In practice, we find few substantive differences across these groups in RDT take-up and composition of ACT buyers, so we pool them together for simplicity.

[21]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.

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 their vouchers had expired, and unused vouchers were collected back from households.[22]

4.2 Baseline Characteristics of Study Sample

In Table 1 we present baseline household characteristics and test for balance across treatment groups. We interviewed the female household head roughly 90 percent of the time. These women are typically married, with five years of education and four dependents. Literacy rates are roughly 60 percent. 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 and lower fraction of infants. Since age is highly correlated with malaria positivity, a lack 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. In all of the results that follow we therefore control for the age of the household head.

4.3 Data

We use three types of data in the analysis that follows. The first is administrative data based on voucher redemptions at the drug shop, the second is an endline survey, and the third is data from "surprise malaria tests" we administered throughout the study period.

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

[22] 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 started.

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). Overall, households in the sample reported 7,733 illnesses. In the analysis below, we will however 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.

"Surprise RDTs" To obtain data on true malaria status among those seeking malaria treatment, a sub-sample of households was randomly selected to get a "surprise RDT". Specifically, if these households came to the drug shop to redeem their ACT voucher, but did not redeem an RDT voucher (either because they didn't have one or because they chose not to) they were asked whether they would be willing to take an RDT for free, after they had paid for the ACT. Over the four-month period during which we conducted this exercise, 93 percent of those offered the surprise RDT consented to be tested (or consented for their sick dependent to be tested). All RDTs were performed by trained study officers posted at the shop. 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.

4.4 Predicting Malaria Positivity

In our data, we can 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. However, constructing estimates of overall overtreatment (OT), undertreatment (UT), and targeting (T) requires data on malaria positivity of *all* illness episodes. To address this, we use data on illness-specific characteristics to impute a malaria probability to the universe of illness episodes enumerated at endline. We impute probabilities

based on the following probit model, fit to all illnesses that were RDT tested at the drug shop (either due to voluntary redemption or surprise testing) over the course of the study:

$$pos_{eh} = \beta_0 + symp'_{eh}\delta + age'_{eh}\lambda + (symp \times over14)'_{eh}\,\gamma + \varepsilon_{eh}$$

where pos_{eh} is a dummy variable equal to 1 if episode e in household h tested RDT positive for malaria, $symp_{eh}$ is a vector of symptom dummies including cough, chills, headache, diarrhea, runny nose, vomiting, body pain, malaise/fatigue, and poor appetite, age_{eh} is a vector including the patient's age, age squared, and 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.[23]

The results of this regression are presented in Table 2. Our estimates are consistent with clinical indicators of malaria (CDC 2011) – chills and body pain are positively correlated with malaria positivity, while cough is robustly negatively correlated with malaria positivity. Table 2 also reveals that age correlates very strongly with malaria positivity. Although the interaction terms make the trend somewhat difficult to infer, children (aged 13 and under) who seek care at the drug shop are substantially more likely to actually have malaria as compared to adults (the relevant fractions testing positive are 38 percent for adults and 83 percent for children). Figure 1 illustrates the strength of this relationship graphically by presenting local linear regression results of malaria positivity on patient age for patients aged 80 and younger. While striking, these results are not entirely 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.

[23]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" and "malaria" are the same – "*homa*". A concern is that if the ACT subsidy increased ACT taking, respondents would be more likely to identify the illness as malaria, and therefore report *homa* as a symptom at endline. 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).

5 Results

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 and an RDT subsidy will depend on where people choose to treat malaria across malaria risk levels. This corresponds in our theoretical framework to the relative value of the three possible malaria treatment-seeking behaviors (buying ACTs at the drug shop, going to the health center, or doing nothing/buying other medicines) across levels of predicted malaria positivity. To get a sense of how these three options compare in the absence of a subsidy, Figure 5 plots the frequency of these three possible actions by predicted positivity among the control ("No Subsidy") group. 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 episode e in household h and $predpos_{eh}$ is predicted positivity. We present the results for all control group households in Panel A, and separately by SES (proxied by head literacy) in Panels B and C. To avoid overweighting households with many illness episodes and to ensure that results are consistent with the analysis that follows, we only include each household's first illness episode following the baseline survey in all the regressions. Solid gray vertical lines demarcate overall tertiles of predicted positivity, while the dashed gray vertical line demarcates the median.[24]

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, while purchase of ACTs at the drug shop slopes upwards only in the top two tertiles of the malaria positivity distribution. We can draw a number of conclusions from these patterns. First, they suggest that our predicted positivity measure captures important heterogeneity in illness episodes that determine 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. For literate households, we therefore expect that the ACT subsidy will have a modest impact on ACT access for the truly sick (a modest decrease in UT, the share of true malaria episodes

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

that remain untreated with an ACT), and a potentially large increase in OT (the share of non-malaria episodes that are treated with an ACT), since most of the crowd out should come from the health center.

The patterns for illiterate households in Panel C are notably different. The share of illness episodes treated at the health center is very low overall and declines sharply in the upper tertile of positivity. 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. The fact that low SES households usually do not seek care at the health center, despite the fact that the health center provides (at least in principle) free ACTs, implies that the cost of visiting the health center must be quite high. Overall, the baseline treatment-seeking patterns we observe among illiterate households suggest that, under an ACT subsidy regime, crowd-out of the health center will be minimal for this group, since they are much less likely to seek care at the health center in any case. Instead, the crowd-out is more likely to come from those that choose non- or sub-therapeutic options. Furthermore, if the ACT subsidy draws high positivity illiterate households to the drug shop (that is, crowd-in from illiterates substantially decreases UT), an ACT subsidy could be quite beneficial in terms of both ACT access and targeting.

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

This section analyzes the impact of introducing a large ACT subsidy in the retail sector. To focus 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 5.3 we will examine the sensitivity of the impacts to the subsidy level). We look at the impact on provider choice (where to seek treatment) and treatment choice. We present the results both graphically (Figures 6 and 7, plotting local linear regressions similar to those presented in Figure 5) and in Tables 3 and 4. The graphs are helpful to see broad patterns. The tables complement the graphs by providing 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,[25] and λ_{strata} are strata fixed effects.

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

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

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.[26]

Recall that households were only given two ACT vouchers and (when relevant) two RDT vouchers. Thus we limit the roster of endline illness episodes to the first episode following the baseline survey to ensure that all households had the option of using a voucher if they so desired. Some households reported more than one member getting sick at once. In these cases, we include all concurrent first episodes, and therefore cluster the standard errors in all illness episode regressions at the household level. Results are similar, though slightly attenuated, if we also include second illness episodes following the baseline survey.

Also note that we exclude from this analysis households who did not receive an RDT voucher but were randomly selected for a surprise RDT test from this analysis, as the results of the surprise test could have impacted their ultimate medication choice.[27]

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 3 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 encouraged care-seeking for a substantial number of illness episodes: the fraction

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

[26] Since the tertile dummies are generated regressors, we present bootstrapped standard errors for all these specifications. We bootstrap by generating 150 replicant datasets where households are sampled with replacement from the core sample. Within each replicant dataset, we recalculate predicted malaria positivity and positivity tertiles.

[27] We do not exclude surprise tested households who received RDT vouchers. Eighty percent of these households chose to use their RDTs when going to the drug shop anyway, and F-tests of the significance of surprise testing selection for the ACT+RDT group confirm that the surprise testing had no significant impact on behavior. Consequently, our results are largely unchanged, though less precisely estimated, when excluding these surprise tested households.

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 in Table 3 present the results broken down by household type (illiterate-headed vs. literate-headed). While the subsidy decreased rates of not seeking care for both illiterate- and literate-headed households (our estimates are just short of marginal significance for illiterates), only literate-headed households were crowded out of the health center, as we had hypothesized given baseline treatment-seeking behaviors.

Figure 6 and the second panel of Table 3 present evidence on how these impacts vary with the underlying malaria probability of the illness episodes. The results are, here again, quite consistent with our theoretical framework. Crowding into the drug shop is most substantial in the first two 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. Note, however, that we cannot reject that crowd-out patterns are the same across tertiles at conventional significance levels.

5.2.2 Impacts on 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 across those most and least likely to have malaria. The results are presented in Figure 7 and in Table 4, and are extremely straightfoward: overall, the subsidy more than doubles the likelihood that an illness is treated with an ACT, and this increase can be seen across the entire spectrum of predicted malaria positivity.

What is particularly striking in Figure 7 is the breakdown by literacy status, which reveals desirable distributional properties of the subsidy: the increase in ACT access is primarily found among the illiterate-headed households (the "poor" in our theoretical framework). The regression results presented in the first panel of Table 4 confirms that the increase in ACT access is significant only among illiterate-headed housheolds. Overall, the retail sector ACT subsidy thus 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 and 10.8 percent respectively), 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, considering that Kenya already has a public-sector subsidy for ACTs. But as discussed earlier, as public health facilities are often far and require costly transportation, the public sector subsidy appears to disproportionately benefit higher SES households.

Table 4 considers two other medication outcomes besides taking an ACT: whether the

illness was treated with some other (less effective) antimalarial or an antipyretic (which could improve symptoms but not clear the malaria infection), or whether it was treated with an antibiotic. Even though overall ACT access did not significantly increase among literate headed households, the subsidy regimes crowded out the use of less effective malaria therapies and antibiotics. This is particulalry true at higher levels of predicted positivity. In the upper tertile of predicted positivity, the subsidy treatments decreased use of substandard malaria therapies among literate-headed households by 29 percentage points and antibiotics by 19 percentage points. Yet at the same time, ACT access did not significantly increase. This could be driven by a "lowest cost first" approach to malaria treatment. Specifically, a household may first treat a suspected case of malaria with an antipyretic or low-cost antimalarial, hoping that the illness gets better. If the illness does not improve, the household may then try taking a more expensive ACT. If literate-headed households were following this approach and the ACT subsidy made ACTs the "first response" choice to suspected malaria cases, this could generate the patterns in our data. (Indeed, we have evidence for this: literate-headed households in the upper tertile of malaria positivity were 14 percentage points less likely to take an ACT *and* a substandard treatment when assigned to the ACT subsidy treatment.)

5.2.3 Summary of Results So Far

To summarize, our results comparing the "ACT subsidy alone" group to the control group imply that:

- The ACT subsidy increases treatment seeking at the drug shop, crowding out no-care among those with a low malaria risk and crowding out health center visits among literate-headed households with an intermediate malaria risk
- The subsidy significantly increases access to ACTs. The gain is particularly pronounced among illiterate-headed households, who have the lowest rates of access in the control group.
- The subsidy leads to a very high rate of overtreatment. Only 38% of adults who take a subsidized ACT are truly malaria positive.

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

5.3 Can a Higher Cost-Share for ACTs Help Limit Overtreatment Without Reducing Access?

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 overtreatment. Answering this question requires estimating the price-elasticity of the demand for ACTs within a range of subsidized prices, and accounting for how different subsidy levels impact undertreatment, overtreatment, and targeting.

5.3.1 Sensitivity of ACT Take-Up to ACT Subsidy Level

We begin by studying how different ACT subsidy levels (within the range of 80 to 92%) impact access. To do so, we make use of two different data sources. First, we use administrative data from the drug shop to determine whether or not higher voucher prices resulted in fewer ACT purchases at the drug shop. 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. Consider increasing the price of an adult ACT dose from Ksh 40 ($0.50, a 92 percent subsidy) to Ksh 100 ($1.25, an 80 percent subsidy). If the marginal episodes crowded out of the drug shop instead 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 overall impacts on access, we exploit our endline data, which includes all illness episodes, irrespective of where they were treated.

Table 5 presents our price-elasticity and targeting results based on both the administrative drug shop data (Panel A) and the endline data (Panel B). In order to focus on within-subsidy impacts, we exclude the control group from this analysis. For the drug shop analysis, we include all households in all treatment arms, and present results of the following regression:

$$\begin{aligned} y_h &= \beta_0 + \beta_1 ACT88_h + \beta_2 ACT80_h + \beta_3 ACT92 \times RDT_h + \beta_4 ACT88 \times RDT_h + \\ &\quad \beta_5 ACT80 \times RDT_h + age_h'\gamma + \lambda_{strata} + \varepsilon_h \end{aligned} \quad (5)$$

where $ACT88_h$, $ACT80_h$, and $ACT92_h$ are dummy variables for the three different ACT subsidy treatments, RDT_h is a dummy variable for the RDT subsidy treatment, and y_h is the outcome of interest. In order to focus on the impact of different ACT subsidy levels, Table 5 omits all coefficients involving RDT dummies (we will discuss these results in subsection 5.4). Panel A of the table presents results for three access outcomes: whether or not a

household used an ACT voucher at the drug shop (this is equal to zero for households who never redeemed any vouchers), whether the household used an ACT voucher for a patient aged 13 and below, and whether the household used an ACT voucher for a patient aged 14 and older. We only consider voucher redemption for the first visit to the drug shop, as surprise testing could have changed a household's subsequent redemption behavior (in practice, the results are virtually unchanged when making use of all voucher redemptions). The first column of Table 5 reveals minimal impacts of higher ACT prices on ACT purchase 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, as illustrated by Figure 2.

A comparison of columns 2 and 3 of Table 5 reveal 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 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.[28] 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. In other words, higher prices help screen out those for whom the expected returns to ACT use are lower: adults.[29]

The analysis based on the endline data presented in the first three columns of Panel B of Table 5, although less precisely estimated, generates similar point estimates and similar patterns of demand by age. This implies that the adults screened out by the higher price at the drug shop did not obtain ACTs elsewhere.

[28]This is because in households that treat all ages, some voucher redemptions for children are not observed because the voucher is 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.

[29]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 shop 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 reasonable that this practice would increase at higher ACT prices. Additional research would be needed to gauge how common partial dosing is, how it is impacted by ACT price, and how to best prevent it.

5.3.2 ACT Subsidy Level and Allocative Efficiency

The last two columns of Table 5 study targeting directly, again making use of both our administrative data (focused on the targeting of retail-sector ACTs) and endline data (which tells us about the targeting of ACTs obtained from either the retail sector or health centers). Regressions presented in these columns are of the same form specified by equation 5, but the sample is limited to ACT takers and the outcome is a measure of malaria positivity (actual surprise RDT test result in column 4, predicted positivity in column 5). We observe that, even though higher prices do not substantially reduce the share of households seeking treatment, the two higher prices are associated with much higher malaria positivity rates: patients for whom care is sought at the drug shop under the 88 and 80 percent subsidy regimes are 18-19 percentage points more likely to be malaria-positive than those patients for whom care is sought at the drug shop under the 92 percent subsidy regime. 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. Even adults seeking care in the lower subsidy groups are substantially more likely to test malaria positive when compared to adult treatment seekers in the highest subsidy group. The results using predicted positivity instead of actual positivity (column 5) are similar to those obtained using actual positivity, but the coefficients are substantially lower. This is to be expected: in Appendix A, we show formally that using predicted positivity (instead of true malaria status) will likely result in coefficients with a downward bias.[30]

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 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 significantly different from zero, possibly due to the downward bias inherent to the use of predicted positivity.

Overall, these results demonstrate that price is 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. We now ask how introducing an RDT subsidy impacts overall access to malaria diagnostic testing and ACT targeting.

[30]The intuition for this result is that true malaria positivity is either 0 or 1, while predicted positivity is never exactly 0 nor 1, so we always underestimate true malaria positivity for those who are malaria positive, and overestimate true malaria positivity for those who are malaria negative, diminishing observed targeting benefits when predicted positivity is used.

5.4 Does Increasing Access to Diagnosis Improve Targeting?

5.4.1 Impacts of the RDT Subsidy on Access to Malaria Testing

The impact of the RDT subsidy on malaria test taking are presented in Figure 8. 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 very straighforward: 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.

One important caveat is that we cannot tell whether health center crowd out leads to reduced use of diagnostic tests for diseases *other* than malaria. Although an RDT test provides a very useful signal as to whether or not to take an antimalarial, households faced with a negative test result may then face a great deal of uncertainty as to what illness they face and what medication choice is appropriate. In this situation, consultation with a trained health professional could be particularly valuable. While we do not have information on what other tests were taken, we can look at how the retail sector RDT subsidy affected visits at the health center. We present these results in Appendix Figure A2. We find marginal evidence that the retail sector RDT subsidy (in the presence of a retail sector ACT subsidy) crowds out health center visits among literate-headed households, but has the reverse effect on illiterate-headed households. None of these effects are statistically significant, however.

5.4.2 Impacts of the 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 9 presents results with respect to RDTs and targeting. In order to clarify the roles of the intensive and extensive margins, we plot estimated malaria positivity first among treatment seekers (those who either took an ACT or a malaria test, Panel B) and then among ACT takers (Panel B) by ACT subsidy level and RDT subsidy status. We show two sets of results per panel. First, we make use of our administrative data (the data collected by surveyors on all households using vouchers at the participating drug shops), presented in the

left column. Again, the advantage of this data is that it includes actual malaria status (from RDT tests performed on patients coming from households selected for a surprise RDT test). It only provides a partial picture, however, since it ignores illness episodes for which care is sought at health centers. We thus also provide results based on our endline data, which has the advantage of including all illness episodes, irrespective of where they were treated, but has the downsides of lacking actual malaria status. The analysis with this data thus relies on predicted positivity (right column). The underlying regression specifications for these graphs thus mirror those presented in the last two columns of Table 5: the analysis in the left column is analogous to the analysis in Panel A of Table 5, and the analysis in the right column is analogous to the analysis in Panel B of Table 5.

Somewhat surprisingly, Figure 9 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). Furthermore, there is no clear pattern in 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 choose to interpret the positive retail-sector targeting impact of the RDT subsidy observed in the presence of an 92% ACT subsidy with caution.[31]

The reason why targeting only marginally improved in the RDT subsidy regime (see Panel B) is that RDT noncompliance in our population was high. While we explicitly advised that patients aged 5 and under take an ACT even when testing negative (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 learning from test results is not 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 lower rate of false negatives (5 percent), it might take some time for households to learn this.

[31] 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. To get a lower bound on the magnitude of the targeting through higher ACT prices, assume that the 12.7 percentage point increase in positivity among treatment seekers associated with the RDT treatment at the highest subsidy level is illusory and that the estimate is entirely due to the 92-percent-ACT-subsidy-only group testing "too negative". Then this would imply that the lower ACT subsidy levels actually increased positivity by around 6 percentage points, rather than 18 percentage points.

Another possible explanation for the high ACT purchase rate after a negative RDT result observed in our experiment 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). Both these issues (lack of information about RDTs and hoarding) could disappear if an ACT+RDT subsidy were implemented as the steady state.

5.5 Results Summary

Figure 10 provides a graphical summary of our targeting results, comparing the distribution of predicted positivity among endline ACT takers in four different policy regimes: no ACT subsidy (the control group), 92 percent ACT subsidy only, 80 percent ACT subsidy only, and 80 percent ACT subsidy + RDT. Overall, the 80 percent ACT subsidy + RDT regime appears to perform the best, though we cannot reject that the distributions are all equivalent.

Taking our point estimates at face value, we estimate that moving from the 92 percent ACT subsidy only regime to the 80 percent ACT subsidy with RDT regime would increase predicted positivity among ACT takers by 5 percentage points (off of a base of 65.8 percent) while leaving the share of illness episodes treated with an ACT virtually unchanged. This estimate relies on predicted positivity and may be a substantial underestimate, 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? The next section takes our estimates and puts them in sharper focus by calculating a variety of cost-effectiveness metrics for the different subsidy regimes.

6 Cost-Effectiveness

In order to assess the benefits of different subsidy regimes, we construct estimates of ACT targeting under three subsidy regimes of interest: 92 percent-no RDT (i.e. the AMFm regime), 80 percent-no RDT, and 80 percent-RDT.[32] Since the subsidy optimization problem is subject to a budget constraint, we also calculate the following measures of subsidy cost:

[32]Note that we do not present estimates of OT and UT. This is because we use a sample of ACT takers to construct predicted positivity. When we use these estimates to impute positivity onto illness episodes that were not treated with ACTs, we arrive at implausibly high estimates of the number of malaria cases in the population. Instead, we use our previous results on ACT access and selection to make inferences about directional changes in OT and UT.

- The subsidy cost per ACT taken by a malaria positive individual
- The share of the total subsidy spent on malaria positive illnesses

The question we ask is the following: since the earlier analysis has revealed that an 80 percent ACT subsidy performs almost as well as a 92 percent ACT subsidy in terms of access among those who have malaria, but reduces overtreatment, should the proposed AMFm subsidy for ACTs be decreased to 80%, and should the saved subsidy money be shifted to RDTs?

The details of the methodology used are presented in Appendix B. The results are presented in Table 6.

Panel A takes our targeting results at face value and presents the associated cost estimates. The RDT regime performs slightly better in terms of targeting, but the gain is not 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 (T) as compared to the same subsidy level plus an RDT subsidy, but costs 19 percent less per malaria positive episode treated with an ACT.

However, 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. It is therefore relevant to consider the potential cost-effectiveness of RDTs in the case where compliance with RDT results is improved. We present the "best case scenario" in Panel B of Table 6, where we assume tested individuals only take ACTs when the RDT is positive. These calculations suggest that RDTs have great potential to limit overtreatment and improve targeting. Furthermore, when RDT compliance is high, the additional cost of subsidizing them is lower as they reduce the number of subsidized ACT doses consumed. Our results suggest that moving from the 92 percent ACT subsidy regime to an 80 percent subsidy combined with RDTs would reduce the cost per ACT to malaria positive person by 5 percent while reducing the share of malaria negative illnesses treated with an ACT by 58 percent. Additional research is needed to understand longer run use of and adherence to RDTs. Without this information, it is difficult to say how close steady state policy could come to our best case scenario.

Another important benefit of RDTs that is not captured by our calculations is that they may increase the likelihood that a non-malaria 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.

7 Conclusion

There is a large class of health issues for which both under-medication and over-medication generate negative spillovers. Under-medication is a public bad for any communicable disease, since the number of untreated individuals increases transmission rates. Over-medication is a public bad whenever the cost of treatment is subsidized. Over-medication is also a public bad when it leads to drug resistance. For this class of health issues, it is thus 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 by far the deadliest in this class of health issues. Malaria kills close to 1 million people each year because of lack of access to effective treatment (World Health Organization 2009). 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 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 one step forward in the direction of answering this question. We use detailed data on treatment-seeking behavior among 2,700 households in a malaria-endemic area of Kenya, combined with an innovative experimental design that enables us 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 elastic at unsubsidized prices, but inelastic over a relatively large range of subsidized prices. This suggests that subsidies for ACTs are clearly needed in order to increase rates of effective treatment among those that suffer from malaria, but these subsidies need not be as large as currently planned by the donor community. Second, 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. Third, 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. Fourth, we find that demand for rapid diagnostic testing is extremely high when it is readily affordable and available.

While our study focused on the demand side, many questions regarding the supply side of the subsidy policy remain unanswered. Additional research is needed to determine how to best implement the subsidy policy to ensure that donor dollars are passed on to consumers, and how to ensure optimal provider incentives. As discussed in Cohen and Dickens (2011),

drug shops, which make a profit from selling ACTs 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 ACT purchases (their incentives would depend on the relative profit margins associated with ACTs and RDTs). The problem of RDT provision is 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). One possibility for increasing RDT provision would be to decouple the supply of medication and diagnostic services. For example, RDTs could be made available at general stores, rather than drug shops, and be made simple enough to use for households to self-administer the test. Alternatively, drug shops might have an interest in building trust and ensuring that their clients' beliefs about the drug's effectiveness remain high. This dynamic incentive could be enough to ensure availability of RDTs at drug shops.

Another important question for future research is that of learning about the effectiveness of ACTs and the reliability of RDTs. Limiting overtreatment with ACTs is likely to improve inference about ACTs' effectiveness among the general population (Adhvaryu 2011). In a companion paper (Cohen et al. 2011) we find that exposure to RDTs via neighbors increases demand for RDTs, but we find no evidence that ACT or RDT exposure impacted individuals' assessments of the quality of ACTs and RDTs. However, our study time frame was quite short, and learning about the quality of ACTs and RDTs might take some time.

A better understanding of the adoption and adherence to RDTs in the long run is important: the results in this paper suggest that bundling the currently proposed ACT subsidy with a subsidy for RDTs could offer a means to extend access to lifesaving medication while limiting wasteful and potentially dangerous overtreatment. However, the results also underscore that the effectiveness of this policy depends on increased adherence to RDT test results. Consequently, understanding how individuals use RDTs in general equilibrium, and whether supporting interventions are needed to increase RDT adherence, will be crucial to futhering the goal of reducing the burden of malaria not only today, but also tomorrow.

References

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

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).

Bleakley, H. (2010). Malaria Eradication in the Americas: A Retrospective Analysis of Childhood Exposure. *American Economic Journal: Applied Economics 2*(45), 1–45.

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

Chandler, C., C. Jones, G. Boniface, K. Juma, H. Reyburn, and C. Whitty (2008). Guidelines and Mindlines: Why do Clinical Staff Over-Diagnose Malaria in Tanzania? A Qualitative Study. *Malaria Journal 7*(1), 53.

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 (2011). Adoption of Over-the-Counter Diagnostics in Africa: The Role of Subsidies, Beliefs, Externalities and Competition. In *The Value of Information*. Resources for the Future.

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

Cohen, J., P. Dupas, and S. Schaner (2011). Information, Peers, and Treatment-Seeking Behavior: Experimental Evidence from Rural Kenya. Mimeo.

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.

Das, J., J. Hammer, and C. Sanchez-Paramo (2011). The impact of recall periods on reported mortality and health seeking behavior. *Journal of Development Economics Forthcoming*.

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. (2010). Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment. Working Paper 16298, National Bureau of Economic Research.

Dupas, P. (2011). Health behavior in developing countries. *Annual Review of Economics 3*, 425–449.

Dupas, P. and J. Robinson (2011). Savings Constraints and Microenterprise Development: Evidence from a Field Experiment in Kenya. Mimeo.

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.

Lucas, A. M. (2010). Malaria Eradication and Educational Attainment: Evidence from Paraguay and Sri Lanka. *American Economic Journal: Applied Economics 2*(2), 46–71.

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.

Otten, M., M. Aregawi, W. Were, C. Karema, A. Medin, W. Bekele, D. Jima, K. Gausi, R. Komatsu, E. Korenromp, D. Low-Beer, and M. Grabowsky (2009). Initial Evidence of Reduction of Malaria Cases and Deaths in Rwanda and Ethiopia Due to Rapid Scale-up of Malaria Prevention and Treatment. *Malaria Journal 8*(1), 14.

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.

Roll Back Malaria (2011). Fact Sheet: Updated ACT Prices Under the Affordable Medicines Facility-malaria, 1 March 2011.

Roll Back Malaria AMFm Task Force (2007). Affordable Medicines Facility-malaria (AMFm): Technical Design. Technical report, Roll Bank Malaria Partnership.

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.

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.

A Predicted Positivity and Regression Bias

One concern with our predicted positivity measure is that the probit model is fit to a selected sample of illness episodes, while we use the results to impute malaria positivity to the universe of illness episodes (including illnesses very unlikely to be malaria, such as allergies). As such, the imputed probabilities are likely biased upwards at the bottom of the distribution. When making ordinal, rather than cardinal, comparisons with respect to predicted probability our measure will still be useful as long as the predicted probabilities are directionally correct. In this case, measurement error in the probabilities should attenuate our results. However, we also wish to use predicted positivity to measure the impact of different subsidy regimes on ACT targeting (the policy parameter T): this is a cardinal comparison.

This Appendix illustrates that as long as predicted positivity is an unbiased measure of actual positivity *conditional on taking an ACT or RDT,* and as long as RDT noncompliance is unrelated to malaria positivity, then targeting estimates will be biased down. This downward bias is confirmed when we compare estimates of targeting at the drug shop using both predicted and actual positivity. We therefore expect that our overall targeting estimates using predicted positivity are lower bounds.

We are interested in differences in outcomes between two groups: ACT subsidy, no RDT ($RDT = 0$) and ACT+RDT subsidy ($RDT = 1$). We make the following assumptions:

1. Predicted positivity is an unbiased measure of a patient's actual malaria probability, *conditional on seeking either an ACT or RDT test* : $E\left[\hat{\pi}_{eh}\right] = \tilde{\pi}_{eh}$.

2. A share Ω of patients in the RDT treatment group choose to take an RDT.

3. 100 percent of patients testing RDT positive for malaria take an ACT (this matches our data).

4. A fraction $\gamma \in [0, 1]$ of patients testing RDT negative for malaria also take an ACT (RDT adherence may depend on $\tilde{\pi}$).

To measure targeting, we wish to estimate the difference in actual malaria positivity among ACT takers in the RDT treatment and control groups. First, consider the sample of episodes that seek malaria treatment (they take an ACT in the control, or they take an ACT or RDT in the treatment). The share of malaria positive individuals who seek care in the control group can be expressed as:

$$E\left[\tilde{\pi} \mid RDT = 0, care = 1\right] \;=\; \Pi_0$$

In the treatment group, there are two subgroups: those who choose to take an RDT ($test = 1$) and those who choose to take an ACT without first redeeming their RDT voucher ($test = 0$). The share of malaria positive individuals in these two groups can be expressed as:

$$\begin{aligned} E\left[\tilde{\pi} \mid RDT = 1, care = 1, test = 0\right] &= \Pi_1^0 \\ E\left[\tilde{\pi} \mid RDT = 1, care = 1, test = 1\right] &= \Pi_1^1 \end{aligned}$$

We can then express overall malaria positivity among care seekers in the RDT treatment group as:

$$E\left[\tilde{\pi} \mid RDT = 1, care = 1\right] = \Omega\Pi_1^1 + (1-\Omega)\,\Pi_1^0 = \Pi_1$$

Note that if the RDT offer changes selection into treatment seeking, we may have $\Pi_1 \neq \Pi_0$. In particular, the RDT may select in "marginal" suspected malaria cases, in which case $\Pi_1 < \Pi_0$.

In the control group, Π_0 is the share of ACT takers who test positive. In the treatment group, the RDT will improve targeting: all of the Π_1 positive episodes will take an ACT, but only $\Omega\gamma\left(1-\Pi_1^1\right) + (1-\Omega)\left(1-\Pi_1^0\right)$ of the negative episodes the will take an ACT. So, the share of ACT takers who are malaria positive in the treatment and control groups can be written as

$$\begin{aligned} S_0 &= \Pi_0 \\ S_1^0 &= \Pi_1^0 \\ S_1^1 &= \frac{\Pi_1^1}{\Pi_1^1 + \gamma\left(1-\Pi_1^1\right)} > \Pi_1^1 \\ S_1 &= \psi S_1^1 + (1-\psi)\,S_1^0 = \frac{\Pi_1}{\Pi_1 + \Omega\gamma\left(1-\Pi_1^1\right) + (1-\Omega)\left(1-\Pi_1^0\right)} > \Pi_1 \end{aligned}$$

where $\psi = \frac{\Omega\left(\Pi_1^1 + \gamma\left(1-\Pi_1^1\right)\right)}{\Omega\left(\Pi_1^1 + \gamma\left(1-\Pi_1^1\right)\right) + (1-\Omega)}$ is the share of treatment group patients taking the ACT who were first tested with an RDT. If we could observe true positivity among all ACT takers, the regression:

$$pos = \beta_0 + \beta_1 RDT + \varepsilon$$

(where we limit the sample to those who take ACTs) would give us what we seek:

$$E\left[\hat{\beta}_1\right] = S_1 - S_0 = \beta_1$$

Which approaches $(1-\Pi_0)$ when $\gamma \to 0$ and $\Omega \to 1$. However, if we can only measure

predicted positivity, we will get:

$$\begin{aligned} E\left[\hat{\beta}_1\right] &= E\left[\hat{\pi} \mid RDT = 1, ACT = 1\right] - E\left[\hat{\pi} \mid RDT = 0, ACT = 1\right] \\ &= E\left[\tilde{\pi} \mid RDT = 1, ACT = 1\right] - E\left[\tilde{\pi} \mid RDT = 0, ACT = 1\right] \end{aligned}$$

where the second equality holds by assumption 1. Furthermore, since there is no screening in the control group: $E\left[\tilde{\pi} \mid RDT = 0, ACT = 1\right] = \Pi_0$. However, RDT-induced screening in the treatment group presents problems. First, we can decompose $E\left[\tilde{\pi} \mid RDT = 1, ACT = 1\right]$ into contributions from the tested and untested groups:

$$\begin{aligned} E\left[\tilde{\pi} \mid RDT = 1, ACT = 1\right] &= (1 - \psi) E\left[\tilde{\pi} \mid RDT = 1, ACT = 1, test = 0\right] + \\ &\quad \psi E\left[\tilde{\pi} \mid RDT = 1, ACT = 1, test = 1\right] \end{aligned}$$

Again, by assumption 1, the untested population poses no problems: $E\left[\tilde{\pi} \mid RDT = 1, ACT = 1, test = 0\right] = S_1^0$. The issue lies with the tested group: expected positivity in the group that actually tests positive will always be less than one (too low), while expected positivity in the group that actually tests negative (but still takes an ACT) will always be greater than zero (too high).

$$\begin{aligned} E\left[\tilde{\pi} \mid ACT = 1, test = 1\right] &= \frac{\Pi_1^1}{\Pi_1^1 + \gamma\left(1 - \Pi_1^1\right)} E\left[\tilde{\pi} \mid ACT = 1, test = 1, pos = 1\right] + \\ &\quad \frac{\gamma\left(1 - \Pi_1^1\right)}{\Pi_1^1 + \gamma\left(1 - \Pi_1^1\right)} E\left[\tilde{\pi} \mid, ACT = 1, test = 1, pos = 0\right] \end{aligned}$$

Now, by assumption 3

$$E\left[\tilde{\pi} \mid ACT = 1, test = 1, pos = 1\right] = E\left[\tilde{\pi} \mid test = 1, pos = 1\right] = \frac{E\left[\tilde{\pi}^2 \mid, test = 1\right]}{\Pi_1^1}$$

Similarly, if we further assume that RDT noncompliance, γ , is unrelated to π

$$E\left[\tilde{\pi} \mid ACT = 1, test = 1, pos = 0\right] = E\left[\tilde{\pi} \mid test = 1, pos = 0\right] = \frac{E\left[\tilde{\pi}\left(1 - \tilde{\pi}\right) \mid test = 1\right]}{1 - \Pi_1^1}$$

putting all of this together

$$E\left[\tilde{\pi} \mid ACT = 1, test = 1\right] = \hat{S}_1^1 = \frac{E\left[\tilde{\pi}^2 \mid ACT = 1, test = 1\right](1 - \gamma) + \gamma\Pi_1^1}{\Pi_1^1 + \gamma\left(1 - \Pi_1^1\right)}$$

since $E\left[\tilde{\pi}^2 \mid ACT = 1, test = 1\right] < \Pi_1^1$, the numerator is less than Π_1^1 so $\hat{S}_1^1 < S_1^1$.

Specifically:

$$\begin{aligned} E\left[\hat{\beta}_1\right] &= \psi\hat{S}_1^1 + (1-\psi)\, S_1^0 - S_0 \\ &= \beta_1 + \psi\left(\hat{S}_1^1 - S_1^1\right) \end{aligned}$$

This illustrates that our targeting estimates will be biased downwards, so much so that the sign of $\hat{\beta}_1$ could actually flip to be negative. Of course, if some of the assumptions that we made are violated in practice, the bias on our targeting estimates may be more complicated. (For example, if RDT noncompliance is positively correlated with π, then we could have $\hat{S}_1^1 > S_1^1$). Very generally, we can decompose the bias on $\hat{\beta}_1$ into three parts: one from estimation of predicted positivity in the control group, one from estimation of predicted positivity among RDT non-takers in the treatment group, and a final part from RDT takers in the treatment group:

$$E\left[\hat{\beta}_1\right] = \beta_1 + \left(S_0 - \hat{S}_0\right) + (1-\psi)\left(\hat{S}_1^0 - S_1^0\right) + \psi\left(\hat{S}_1^1 - S_1^1\right)$$

B Methodolgy used for Cost-Effectiveness Analysis

Among the first illness episode sample, we run regressions according to

$$y_{eh} = \beta_0 + \beta_1 ACTprice_h + \beta_2 RDT_h + \beta_3 ACTprice \times RDT_h + age'_h\gamma + \lambda_{strata} + \epsilon_{eh}$$

where $ACTprice_h$ is the randomly assigned price (in US$) of an adult dose of ACTs on household h's voucher. Outcomes of interest include (1) the share of episodes treated with an ACT, (2) the share of episodes treated with an RDT, and (3) predicted positivity among ACT/RDT takers and non-takers. We then predict values of each outcome for each ACT-RDT subsidy regime included in our experimental design. Since the subsidy cost of ACTs, malaria positivity, and the price elasticity of ACT demand varies with patient age, we perform these calculations separately for adults (aged 14 and older) and children (aged 13 and younger).[33]

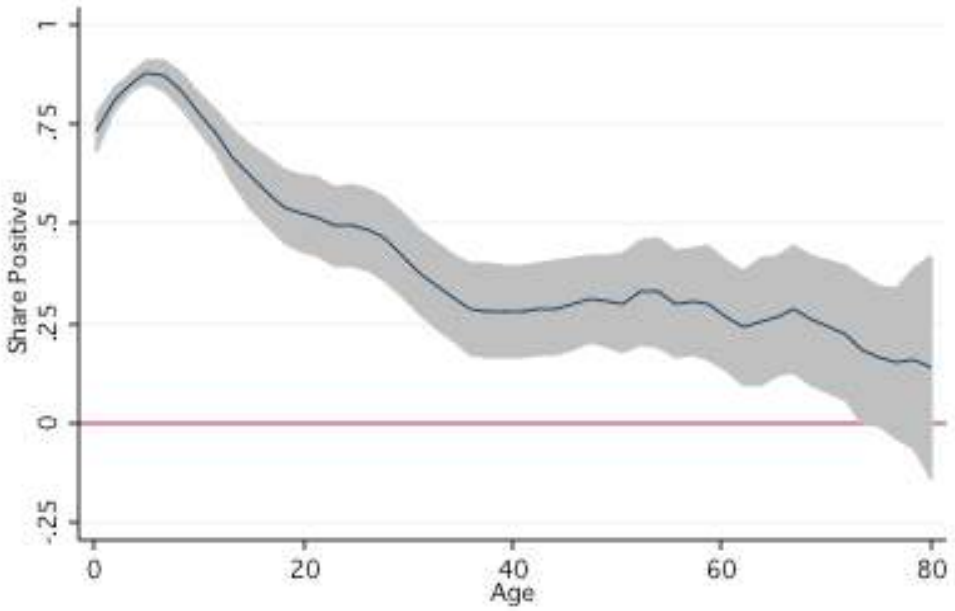
In terms of costs, we assume that each RDT costs $0.53 to subsidize. This is equal to 85 percent of the cost we paid (including shipping) to obtain the RDTs – subsidizing RDTs on a very large scale could bring this cost down since we only ordered a small quantity of tests.[34] The Global Fund currently provides two different scenarios for per-dose subsidy amounts (Roll Back Malaria 2011). For each age group we took the midpoint of the two scenarios, assumed this would be the subsidy cost in our 92 percent scenario, and scaled the other subsidy amounts accordingly. We then combined the subsidy cost and demand/targeting estimates and aggregated up to the population level using the observed age distribution of illness episodes to calculate our measures of subsidy performance.

In addition to our ordinary estimates, we calculated cost effectiveness measures for the ACT+RDT regimes in a "perfect adherence" scenario. Here, we assumed that demand for RDTs was unchanged, but that compliance with test results was perfect, in that only patients who test malaria positive take ACTs.

[33] As illustrated by Figure A1, ACTs come in 4 different dose sizes, determined by age. Since we do not have sufficient sample size to estimate predicted outcomes for each age group separately, we assume that outcomes are equivalent for all young children. We then combine these estimates with the age distribution in the population and the four different dose sizes to calculate cost effectiveness metrics. We also note that if our predicted positivity measure overestimates the share of non-ACT treated episodes that are malaria, then our estimates of both OT and UT will be biased upwards. We therefore focus on directional changes in these measures across different subsidy regimes rather than absolute numbers.

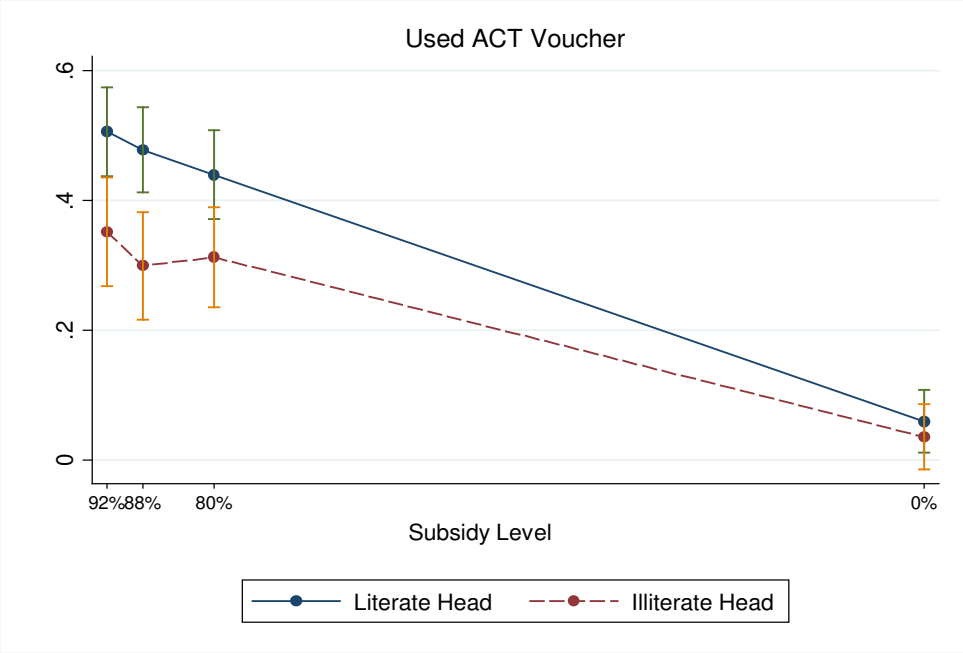
[34] We chose 85 percent of our cost because RDT demand was virtually unchanged when households were asked to pay 15 percent of the cost of RDTs instead of receiving an RDT for free. Additional research would be needed to determine the optimal subsidized price of RDTs, but our results make clear that the optimal price need not be zero.

Figure 1. Among those purchasing an antimalarial at the drug shop: share actually malaria positive (by age)



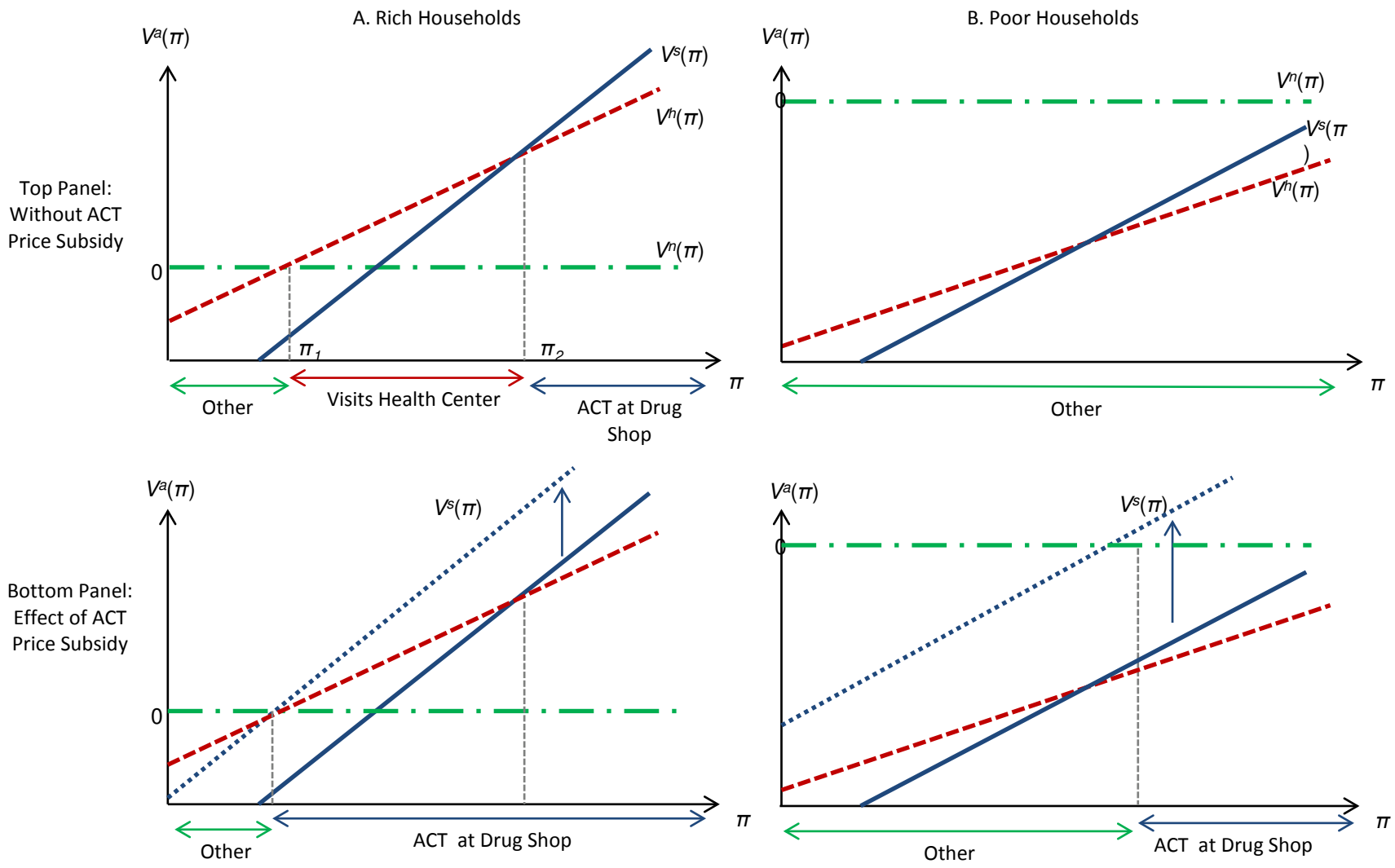
Notes: Local linear regression results for patients aged 80 and younger. Gray shading indicates a 95 percent confidence interval.

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



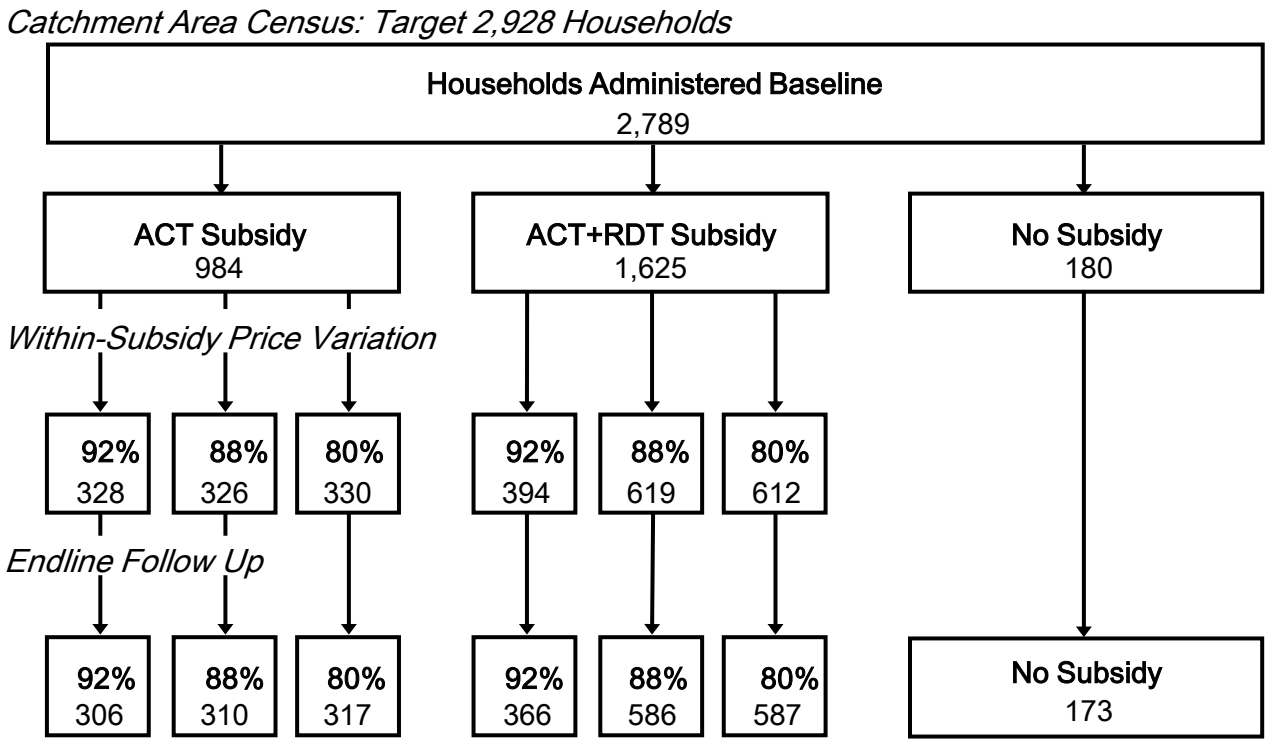
Notes: Figure plots predicted values and 95 percent confidence intervals from regression estimates using heteroskedasticity robust standard errors. 92%, 88% and 80% subsidies correspond to 40Ksh ($0.50), 60 Ksh ($0.75) and 100 Ksh ($1.25) for an adult dose, respectively. Regressions include controls 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



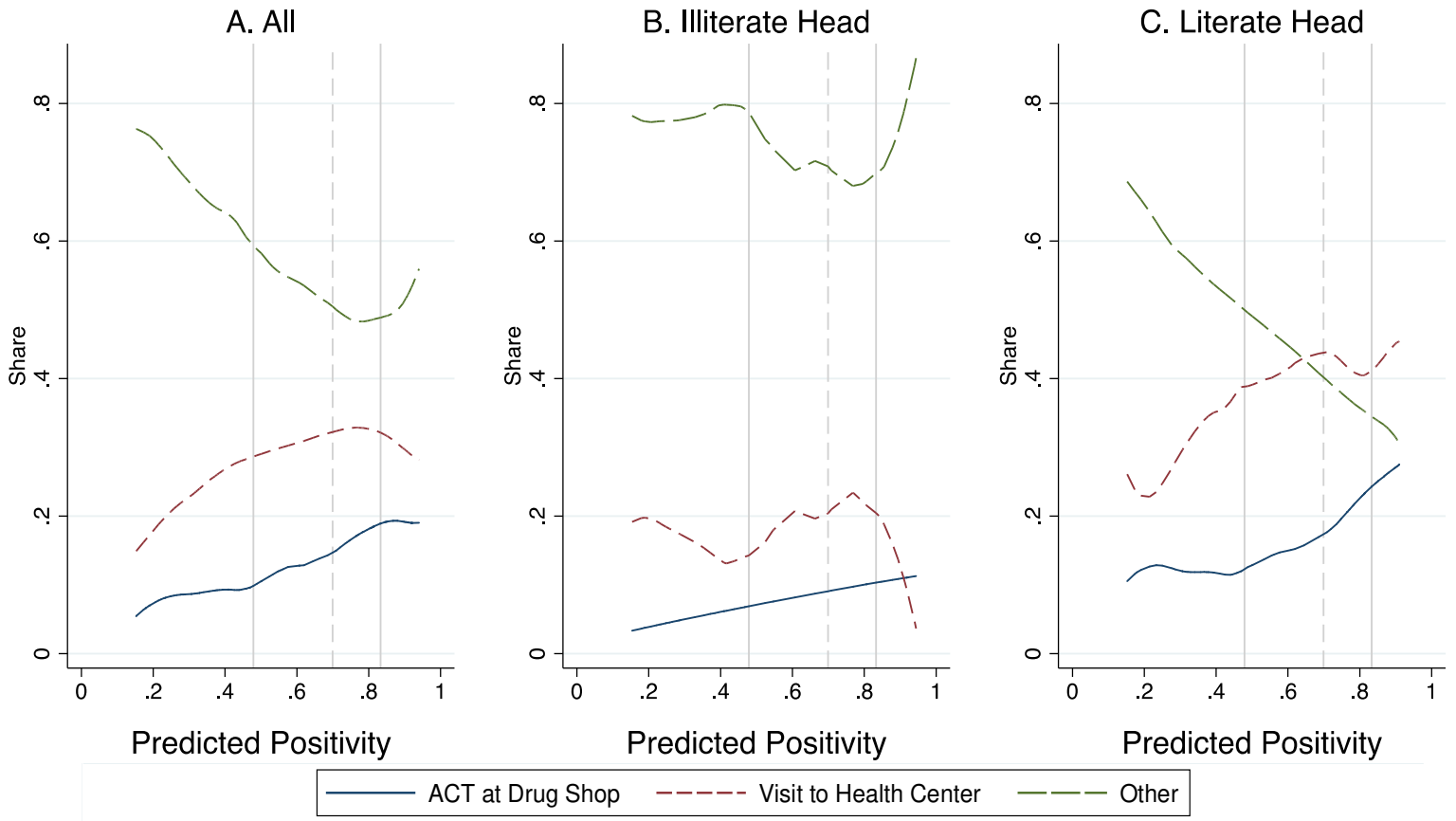
Notes: π is the (perceived and actual) probability that the illness episode is malaria. V^s is the value of purchasing an ACT at the drug shop; V^h is the value of visiting a health center and receiving free ACT if positive; V^n is the value of doing neither of the two options above. The value functions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

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



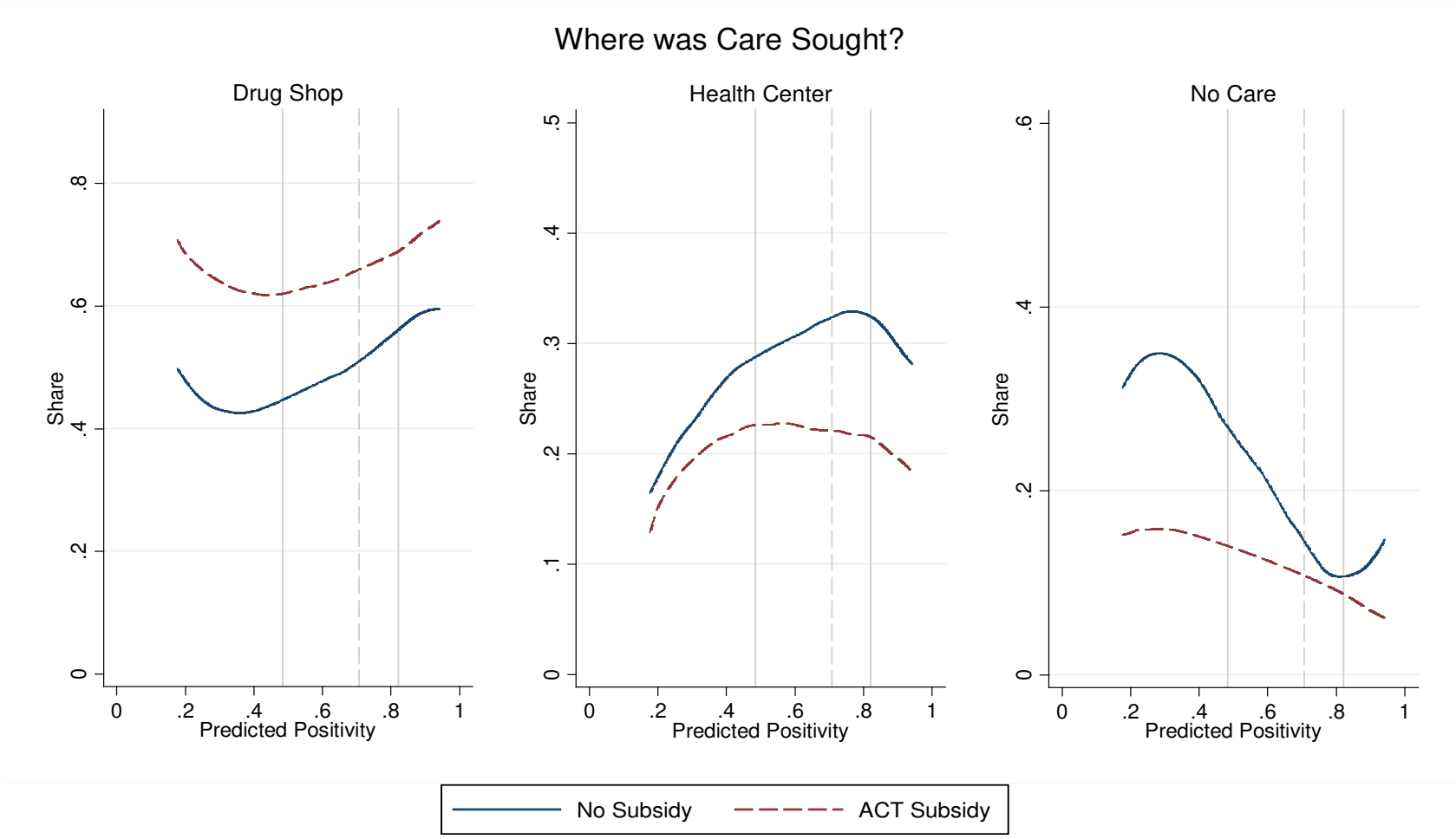
Notes: 49 percent of ACT subsidy only households and 80 percent of ACT+RDT Subsidy households were selected for surprise RDT testing at the drug shop.

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



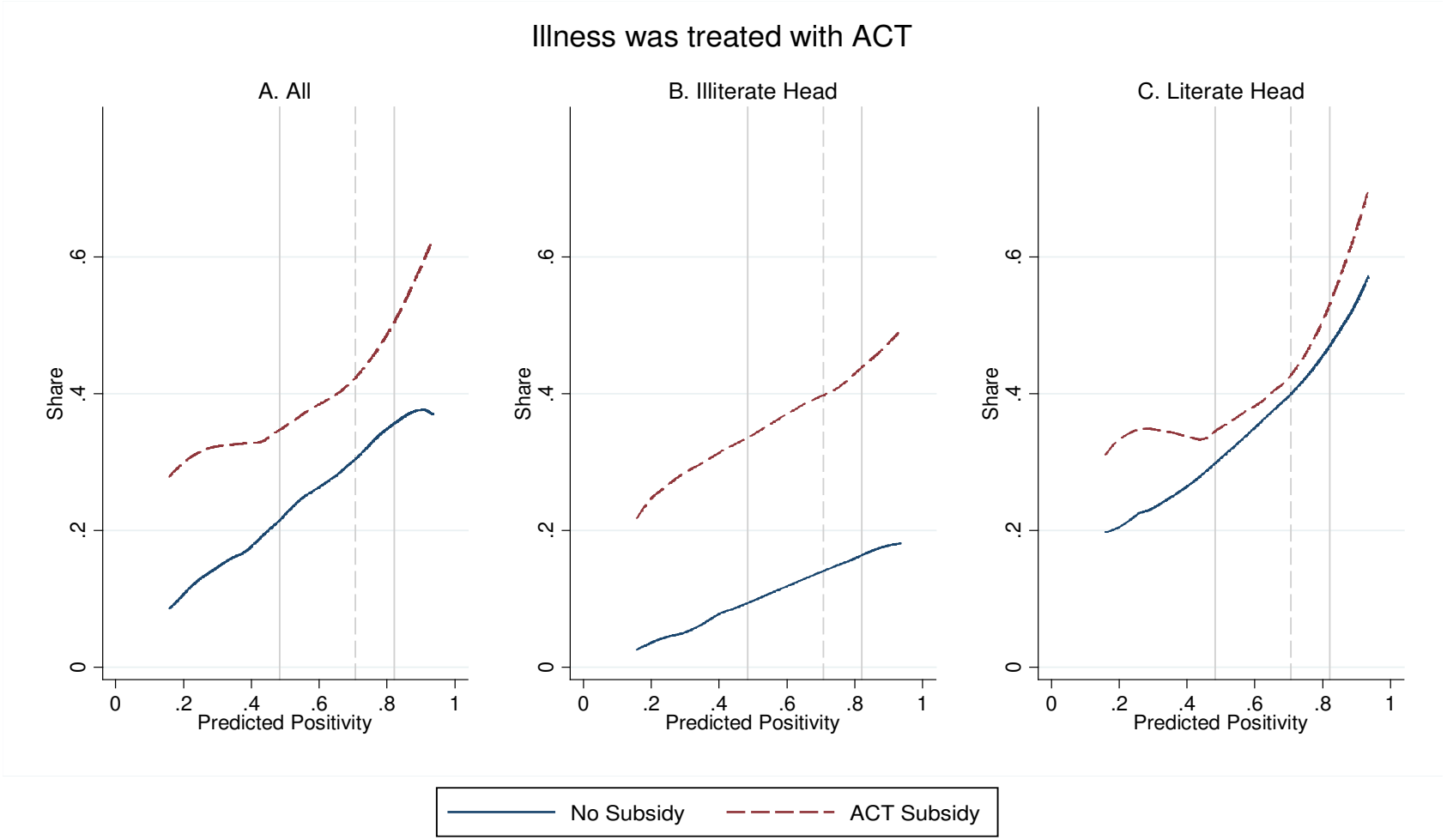
Notes: Data from "No Subsidy" group. Local linear regression lines trimmed at 2.5 percent. Tertiles demarcated by gray vertical lines. Median demarcated by dashed gray vertical line.

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



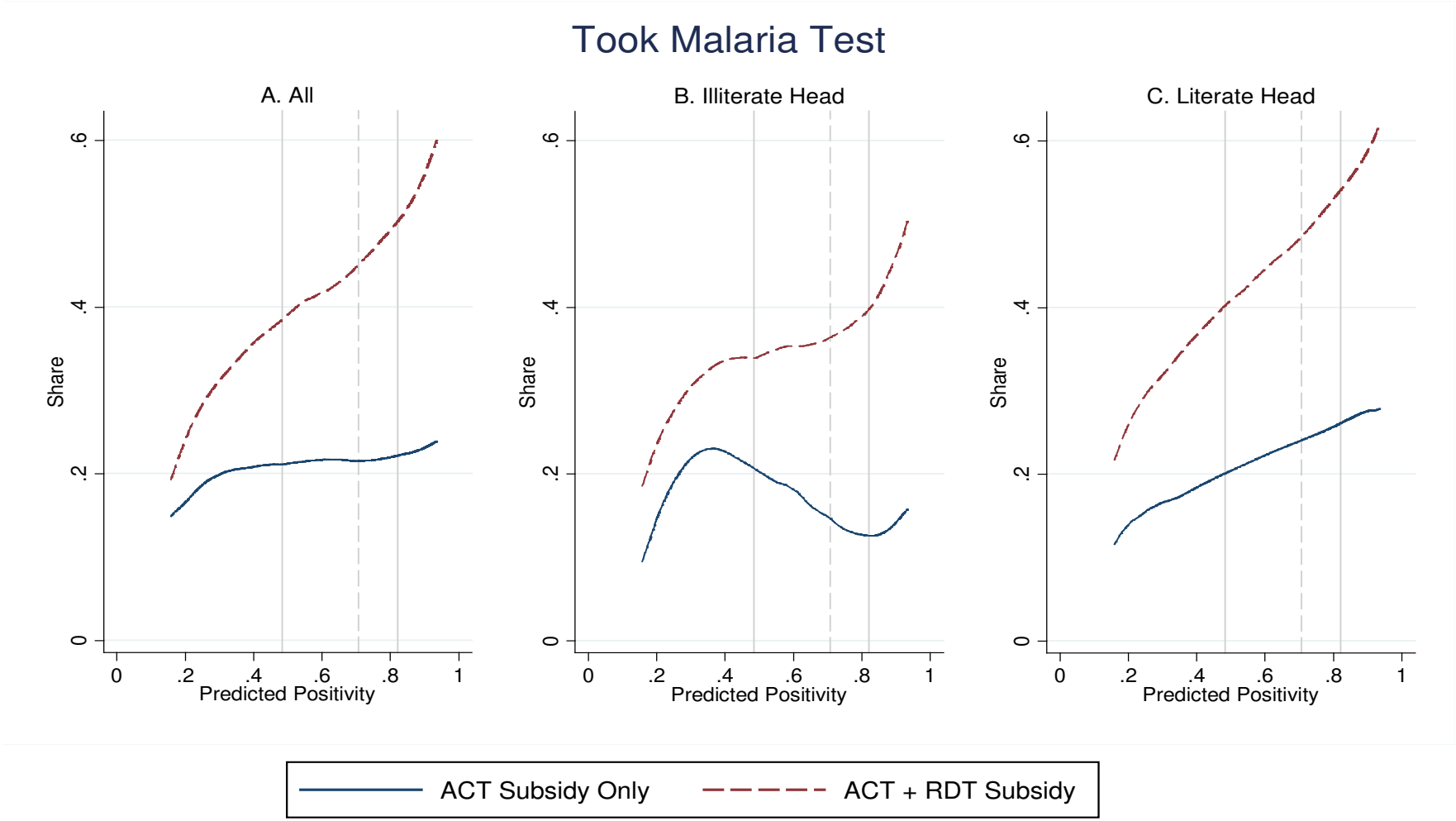
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Dashed gray vertical line shows median. Excludes households randomly selected for surprise RDT testing at drug shop.

Figure 7. Impact of Retail Sector ACT Subsidy on ACT Access



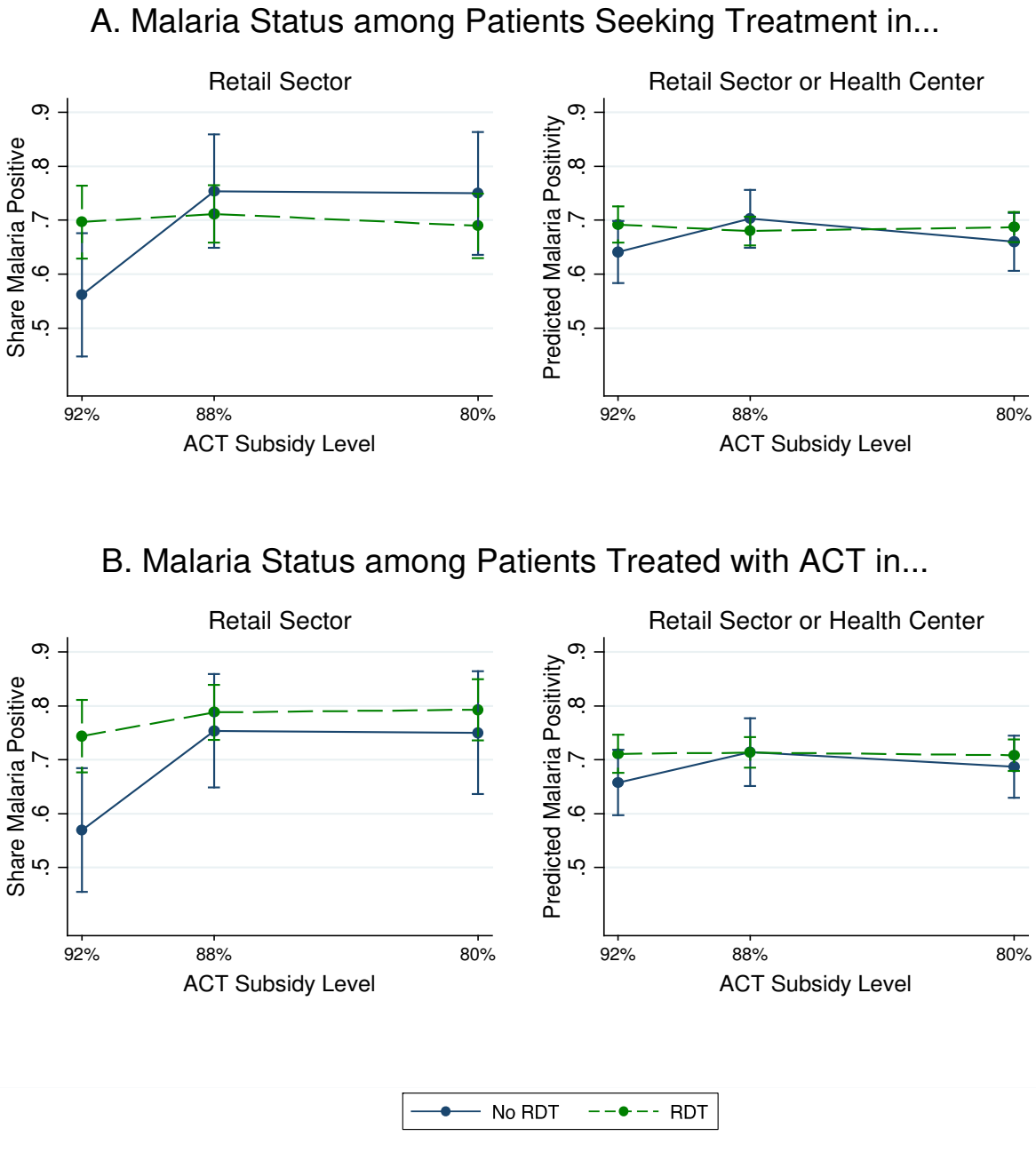
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Dashed gray vertical line shows median. Excludes households randomly selected for surprise RDT testing at drug shop.

Figure 8. Impact of Retail Sector RDT Subsidy on Malaria Testing



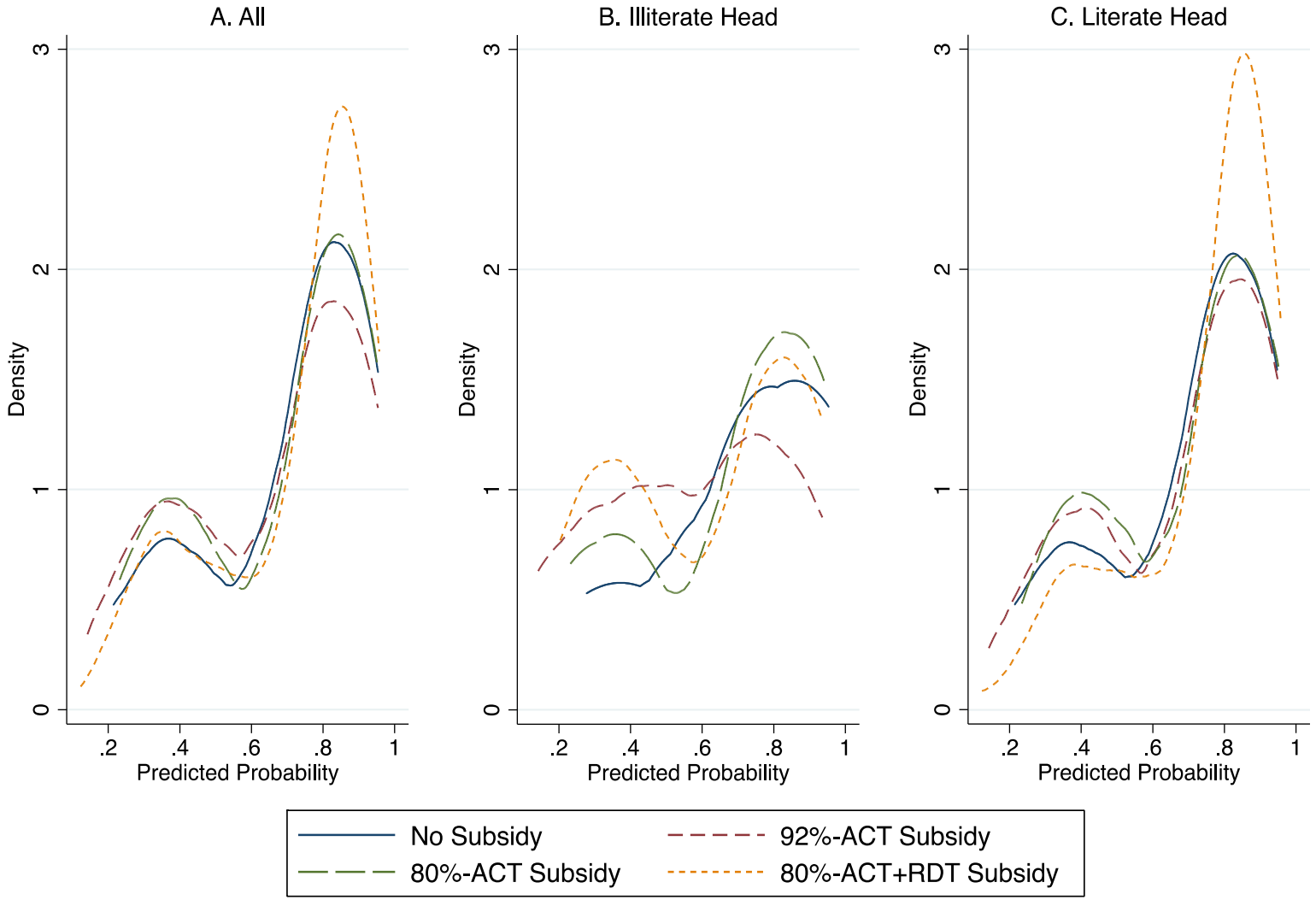
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Dashed gray vertical line shows median. Excludes households without RDT vouchers but randomly selected for surprise RDT testing at drug shop.

Figure 9. 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 10. Distribution of Predicted Positivity Among ACT Takers by Subsidy Treatment



Notes: Excludes households without RDT vouchers but randomly selected for surprise RDT testing at drug shop.

Table 1. Summary Statistics

	Control Group (C)	ACT Subsidy Only (T1)	ACT Subsidy + RDT Subsidy (T2)	P-value (C=T1)	P-value (C=T2)	P-value (T1=T2)	N
Characteristics of Interviewed Household Head							
Female	0.867	0.895	0.907	0.292	0.125	0.333	2789
Age (years)	41.7	38.8	38.8	0.041**	0.036**	0.981	2646
Education (years)	5.10	5.36	5.54	0.424	0.158	0.253	2774
Literate	0.575	0.621	0.621	0.258	0.236	0.973	2782
Married	0.783	0.789	0.777	0.860	0.841	0.456	2784
Number Dependents	4.12	4.07	4.13	0.822	0.979	0.586	2663
Household Characteristics							
Number members	5.48	5.29	5.34	0.382	0.521	0.585	2789
Fraction Adults (Ages 14+)	0.623	0.582	0.580	0.044**	0.029**	0.836	2337
Fraction Infants (Under 4)	0.113	0.139	0.141	0.033**	0.018**	0.790	2337
Acres Land	2.72	2.08	2.28	0.045**	0.175	0.087*	2250
Distance from drug shop (km)	1.68	1.66	1.67	0.873	0.966	0.809	2788
Distance from closest clinic (km)	6.57	6.55	6.60	0.919	0.891	0.635	2785
Baseline Malaria Knowledge and Health Practices							
Number bednets	1.77	1.77	1.78	0.994	0.929	0.875	2784
Share HH members slept under net	0.561	0.585	0.573	0.450	0.698	0.455	2661
Heard of ACTs	0.399	0.425	0.427	0.519	0.467	0.904	2771
Heard of RDTs	0.128	0.153	0.140	0.365	0.646	0.375	2786
Treats water regularly	0.408	0.390	0.416	0.648	0.841	0.190	2779
Number of presumed malaria episode last mon	1.20	1.20	1.23	0.985	0.744	0.508	2789
Cost Per Episode (Among Those Seeking Any care)							
Total Cost (US $)	1.63	1.54	1.68	0.694	0.825	0.405	1319

Notes: Household averages. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.
The exchange rate at the time of the study was around 78 Ksh to US$1.

Table 2. Predicting Malaria Positivity - Probit Marginal Effects

	Coefficient	Standard Error
Cough	-0.107***	(0.038)
Chills	0.096**	(0.043)
Headache	0.021	(0.048)
Diarrhea	-0.031	(0.046)
Runny Nose	-0.020	(0.066)
Vomiting	0.008	(0.033)
Body Pain	0.118	(0.085)
Malaise	-0.051	(0.087)
Poor Appetite	-0.013	(0.038)
Age 14 or Above	-0.017	(0.127)
Age	0.081***	(0.017)
Age Squared	-0.007***	(0.001)
(Age 14 or Above) x Cough	0.017	(0.062)
(Age 14 or Above) x Chills	-0.051	(0.074)
(Age 14 or Above) x Headache	0.016	(0.065)
(Age 14 or Above) x Diarrhea	0.057	(0.093)
(Age 14 or Above) x Runny Nose	-0.365	(0.240)
(Age 14 or Above) x Vomiting	0.074	(0.051)
(Age 14 or Above) x Body Pain	-0.168	(0.131)
(Age 14 or Above) x Malaise	0.055	(0.091)
(Age 14 or Above) x Poor Appetite	0.052	(0.075)
(Age 14 or Above) x Age	-0.094***	(0.018)
(Age 14 or Above) x Age Squared	0.007***	(0.001)
DV Mean / N	0.702	1386

Notes: Standard errors in parentheses. Sample includes all individuals who were tested with an RDT by the research team at the drugstore and had nonmissing symptom and age data. ***, **, and * indicate significance at the 99, 95, and 90 percent

Table 3. Impact of ACT Subsidy on Treatment Seeking by Literacy and Predicted Malaria Probability

	All			Illiterate			Literate		
	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***	0.072	0.002	-0.096	0.215***	-0.135***	-0.085*
	(0.045)	(0.042)	(0.035)	(0.071)	(0.055)	(0.059)	(0.061)	(0.055)	(0.047)
Specification 2 - Impact by Predicted Probability									
α_1 ACT Subsidy * Lower Tertile	0.195***	-0.021	-0.186***	0.054	0.081	-0.153	0.298***	-0.088	-0.221***
	(0.082)	(0.067)	(0.068)	(0.124)	(0.088)	(0.110)	(0.104)	(0.099)	(0.092)
α_2 ACT Subsidy * Middle Tertile	0.174*	-0.190*	0.016	0.094	-0.225	0.132	0.200*	-0.184	-0.018
	(0.096)	(0.099)	(0.069)	(0.172)	(0.143)	(0.121)	(0.114)	(0.116)	(0.086)
α_3 ACT Subsidy * Upper Tertile	0.075	-0.042	-0.047	0.023	0.027	-0.097	0.123	-0.135	0.011
	(0.085)	(0.084)	(0.049)	(0.144)	(0.112)	(0.097)	(0.123)	(0.116)	(0.059)
p-val: α1 = α2 = α3	0.562	0.417	0.128	0.959	0.233	0.233	0.498	0.842	0.104
DV Mean (Control Group)	0.494	0.290	0.216	0.585	0.154	0.262	0.438	0.375	0.188
N	2042	2042	2042	705	705	705	1332	1332	1332

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. Boostrapped standard errors clustered at the household level in parentheses. All regressions control for household head age, RDT treatment status, and a full set of strata dummies. Tertile cutoffs are illustrated in Figure 5. The distribution of first episodes between tertiles 1, 2, and 3 is 27.0, 36.6, and 36.5 percent for literate households and 45.8, 27.8, and 26.4 percent for illiterate households. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 4. Impact of ACT Subsidy on Medication Choice by Literacy and Predicted Malaria Probability

	All			Illiterate			Literate		
	Illness treated with ACT	Illness treated with Other Anti-malarial or Anti-pyretic	Illness treated with Antibiotic	Illness treated with ACT	Illness treated with Other Anti-malarial or Anti-pyretic	Illness treated with Antibiotic	Illness treated with ACT	Illness treated with Other Anti-malarial or Anti-pyretic	Illness treated with Antibiotic
Specification 1 - Main Effect									
α ACT Subsidy	0.153***	-0.052	-0.071**	0.272***	-0.008	-0.062	0.081	-0.092	-0.089*
	(0.040)	(0.048)	(0.036)	(0.058)	(0.085)	(0.056)	(0.053)	(0.059)	(0.046)
Specification 2 - Impact by Predicted Probability									
α_1 ACT Subsidy * Lower Tertile	0.157***	0.055	-0.050	0.223***	-0.003	-0.009	0.122	0.089	-0.084
	(0.063)	(0.088)	(0.055)	(0.078)	(0.135)	(0.082)	(0.100)	(0.118)	(0.079)
α_2 ACT Subsidy * Middle Tertile	0.112	-0.099	-0.059	0.211	0.016	-0.154	0.058	-0.133	-0.028
	(0.091)	(0.102)	(0.082)	(0.155)	(0.180)	(0.153)	(0.109)	(0.123)	(0.091)
α_3 ACT Subsidy * Upper Tertile	0.161*	-0.177**	-0.118	0.331***	-0.062	-0.064	0.024	-0.286***	-0.189**
	(0.090)	(0.079)	(0.072)	(0.133)	(0.132)	(0.089)	(0.114)	(0.097)	(0.096)
p-val: α1 = α2 = α3	0.921	0.144	0.742	0.782	0.921	0.703	0.808	0.048**	0.491
DV Mean (Control Group)	0.259	0.494	0.185	0.108	0.446	0.138	0.365	0.531	0.219
N	2042	2042	2042	705	705	705	1332	1332	1332

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. Bootstrapped standard errors clustered at the household level in parentheses. All regressions control for household head age, RDT treatment status, and a full set of strata dummies. Tertile cutoffs are illustrated in Figure 5. The distribution of first episodes between tertiles 1, 2, and 3 is 27.0, 36.6, and 36.5 percent for literate households and 45.8, 27.8, and 26.4 percent for illiterate households. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 5. Impact of Variation in 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
ACT Subsidy = 88%	-0.027	0.032	-0.058**	0.187**	0.068*
	(0.038)	(0.034)	(0.027)	(0.080)	(0.041)
ACT Subsidy = 80%	-0.055	0.027	-0.082***	0.182**	0.102***
	(0.037)	(0.034)	(0.026)	(0.084)	(0.040)
Mean DV (ACT 92%, no RDT)	0.439	0.268	0.171	0.563	0.643
N	2609	2609	2609	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
ACT Subsidy = 88%	-0.042	0.001	-0.128		0.057
	(0.060)	(0.081)	(0.087)		(0.044)
ACT Subsidy = 80%	-0.017	0.021	-0.091		0.030
	(0.058)	(0.080)	(0.083)		(0.043)
Mean DV (ACT 92%, no RDT)	0.457	0.462	0.450		0.658
N	1880	1085	794		816

Notes: Panel A: The unit of observation is the household. 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 6. Cost Effectiveness Estimates

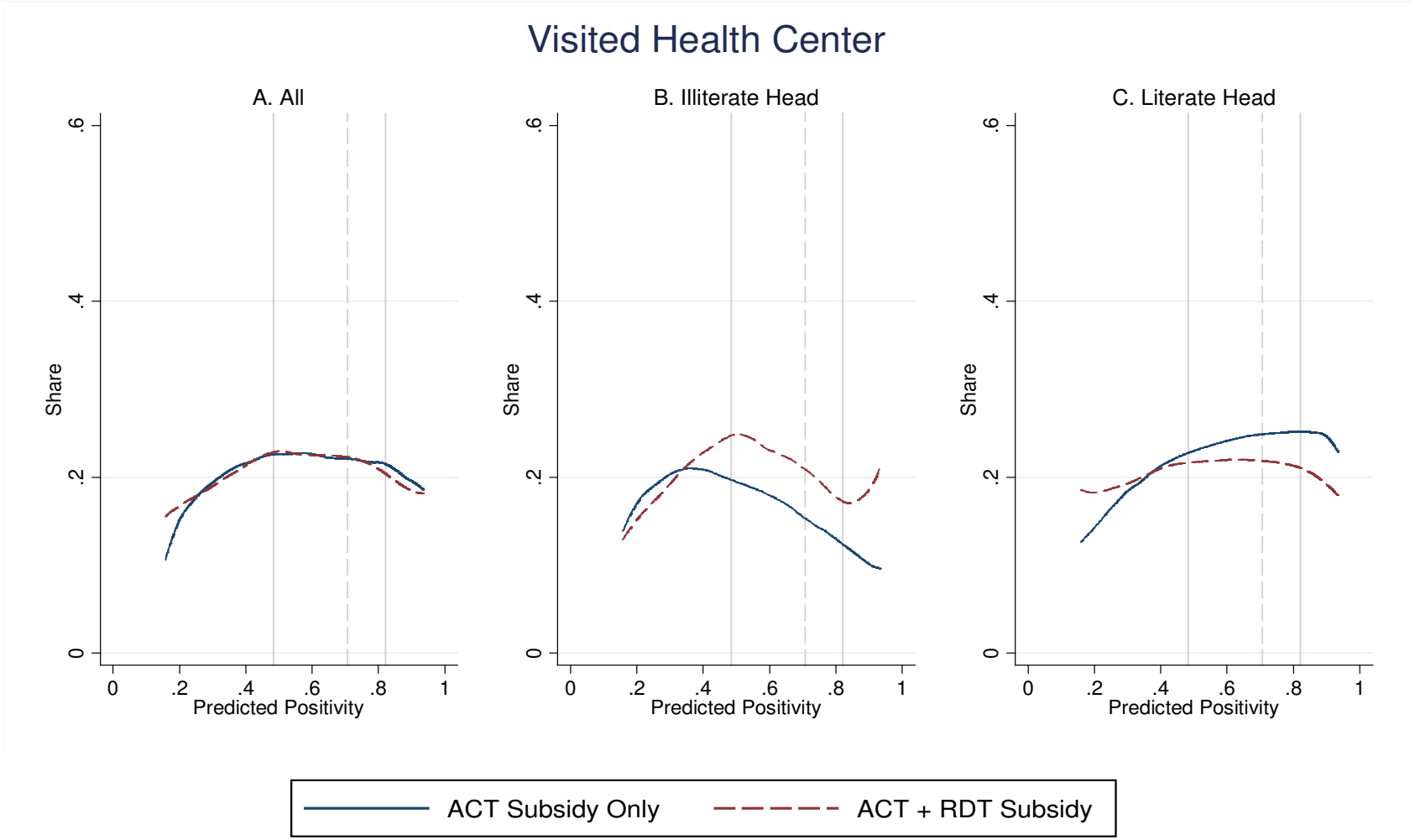
	T: Fraction of ACT Takers that are Malaria+	Cost/ACT to Malaria Positive Episode	Share of Total Subsidy Budget Spent on Malaria+ Episodes
A. Actual RDT Adherence			
ACT 92%	0.676	1.49	0.605
ACT 80%	0.711	1.25	0.653
ACT 80% - RDT	0.713	1.55	0.669
B. Perfect RDT Adherence			
ACT 92%	0.683	1.48	0.609
ACT 80%	0.727	1.21	0.674
ACT 80% - RDT	0.799	1.42	0.735

Notes: See main text and Appendix B for details of the methodology used and assumptions made. The perfect RDT adherence scenario assumes perfect compliance with RDT test results (for ACT-RDT regimes only) and no change in RDT takeup.

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

Figure A2. Impact of Retail Sector RDT Subsidy on Health Center Visits



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 but randomly selected for surprise RDT testing at drug shop.

Appendix Table A1. Baseline Treatment Seeking Behavior

		By Household SES			By Patient's Age		
	All	Iliterate	Literate	p-value Illit.=Lit	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	0.994	1.36	0.000***	0.617	0.568	--
At least one presumed malaria episode last month	0.685	0.600	0.739	0.000***	0.435	0.387	--
HH member took RDT test in last month (if reported malaria)	0.040	0.038	0.041	0.732	--	--	--
HH member took microscopy test in last month (if reported mala	0.251	0.202	0.275	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: Comparison Across Subsidy Levels

	Reported Any Illness Episode	Number Episodes Reported	Predicted Malaria Positivity - First Episode	Days Ago - First Episode	Patient Age - First Episode
ACT 92%	0.015	0.024	0.037	1.73	-1.71
	(0.020)	(0.157)	(0.023)	(3.86)	(1.65)
ACT 88%	0.002	-0.063	0.039*	4.72	-2.92*
	(0.021)	(0.155)	(0.023)	(3.75)	(1.61)
ACT 80%	-0.020	-0.168	0.031	3.19	-1.69
	(0.021)	(0.155)	(0.023)	(3.78)	(1.62)
Any RDT	0.006	-0.025	0.004	-1.27	0.906
	(0.010)	(0.078)	(0.010)	(1.87)	(0.777)
Ex-Post Tested	0.001	0.089	-0.017	5.09***	0.988
	(0.010)	(0.079)	(0.011)	(1.95)	(0.797)
P-value (92=88=80)	0.005***	0.101	0.765	0.388	0.221
DV Mean	0.950	3.05	0.627	64.7	19.1
N	2621	2621	2473	2438	2473

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.