

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

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Abstract

In response to widespread resistance to older anti-malarials, the global health community is planning to make new, more effective malaria treatments called Artemisinin Combination Therapies (ACTs) available at heavily subsidized rates throughout Africa. Highly-subsidized ACTs accessed through the private sector may go a long way toward reducing malaria-induced mortality and morbidity. However, lower-priced ACTs are also likely to increase inappropriate treatment, wasting subsidy dollars and potentially contributing to drug resistance. This paper uses data from a randomized controlled trial conducted with over 2,700 households in rural Kenya to study the tradeoffs between ACT affordability and overuse. We compare the proposed ACT subsidy policy to an alternative policy regime that explicitly acknowledges the problem of overuse by providing access to a subsidized rapid diagnostic test for malaria (RDT) in tandem with subsidized ACTs. We find that ACT access increases by 59 percent in the presence of an ACT subsidy of 80 percent or more. Under the proposed ACT subsidy policy, however, only 56 percent of those buying an ACT at the drug shop test positive for malaria. We show that this share increases (without substantially compromising access) to 81 percent when the ACT subsidy is somewhat reduced and accompanied by an RDT subsidy.

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1 Introduction

Limiting the spread of infectious disease has positive social benefits – as such, infectious disease programs often feature subsidies for prevention and treatment technologies. Financing such subsidies is obviously subject to a budget constraint, however, and it is therefore critical 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 can contribute 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 the treatment is subsidized and thus affordable, provided side-effects are minimal. 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 the 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 (quinine, 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. 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 is prohibitive for the great majority of rural African households 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 chil-

¹Combination 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).

dren with malaria were treated with ACTs (World Health 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 private sector, as many people seeking malaria treatment do so in loosely regulated, informal private-sector 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 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 (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.

We use data from a randomized controlled trial conducted with over 2,700 households in rural Kenya to study the tradeoffs between ACT affordability and overuse in the context of the AMFm subsidy. Our research design also tests an alternative to the AMFm subsidy regime that explicitly acknowledges 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 technologies, 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 financed by reducing the ACT subsidy somewhat, an approach that could be more cost-effective than the proposed AMFm subsidy alone, especially since the modest decreases in the ACT subsidy that we study improve the targeting of ACTs to those most likely to have malaria without meaningfully reducing ACT access.

²RDTs for malaria work similarly to rapid tests for HIV and do not require specialized equipment, such as a microscope, or electricity.

This is primarily due to two stark results from our experiment:

1. Over-diagnosis of malaria is extremely common in our study context, particularly among teenagers and adults. 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 highly price-elastic above a certain range (which includes the unsubsidized price of ACTs), but very inelastic at low prices, especially for children. 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.

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. 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. 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 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, in the absence of any information or marketing campaign on RDTs, our estimates suggest that moving from the AMFm subsidy level to an 80 percent ACT subsidy with RDTs could increase 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. Overall, our results suggest that, in this context, taking some of the planned ACT subsidy money away from ACTs and putting it towards subsidizing and promoting RDTs could improve targeting and be particularly cost-effective among adults provided adherence to test results can be improved.

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 neediest. We proxy SES 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 regime disproportionately increases access among illiterate headed households. Consequently, literate-headed households are just 17 percent more likely to treat an illness with an ACT when ACTs are subsidized. The 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 proposed 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, our paper adds to a fast-growing experimental literature on user fees for health services and health products whose appropriate use generates positive externalities. So far this literature has focused on optimal pricing for preventative health products, such as water purification kits or bednets,³ 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. In contrast, this paper considers the price-setting problem that arises when overuse generates negative externalities (in our case, through drug resistance). Second, we contribute to the literature

³See 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.

on underdiagnosis and overtreatment, two major contributors to health care costs and a source of concern throughout the world (Welch, Schwartz, and Woloshin 2011). Finally, we contribute to the nascent literature on treatment-seeking behavior in resource-constrained environments, along with the earlier contributions of Leonard, Mliga, and Mariam (2002) in Tanzania, Banerjee, Deaton, and Duflo (2004) in Rajasthan (India), and of Leonard (2007, 2009) in Tanzania and Cameroun, respectively.

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.

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, as discussed in the introduction, the vast

majority of children under the age of 5 with presumed malaria are not treated with effective antimalarial drugs. This crisis in access has been intensified by the spread of drug resistant malaria parasites. Early malaria control efforts relied heavily on chloroquine as a cheap, effective treatment. *Plasmodium falciparum*, by far the most common and deadly of the five strains of malaria, started becoming resistant to chloroquine in the 1960s and rendered the drug ineffective by the early 1990s, contributing to a substantial rebound in malaria mortality (Trape 2001). Subsequent innovations in antimalarial medicines have been successively less able to withstand parasite resistance (D’Alessandro and Buttiens 2001).

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.⁴ In most populations dealing with endemic malaria this cost of treatment is unaffordable.

2.2 The Affordable Medicines Facility for Malaria (AMFm)

As discussed in the introduction, the two major challenges in malaria control today are: (1) How can effective malaria medicines be made accessible and affordable? And (2) How can resistance to the only remaining effective treatment be forestalled?

In response to these two challenges, in 2007 the Gates Foundation, UNICEF, the Global Fund, and others designed a “global subsidy” policy called the Affordable Medicines Facility for Malaria (AMFm). Through a co-payment to ACT manufacturers, the program aims to reduce the price of ACTs by roughly 95 percent to first line buyers, such as governments, NGOs and wholesalers (Global Fund to Fight AIDS, TB and Malaria 2010). The final price to consumers in the private sector is unrestricted, but the aim is for retail sector ACTs to be cheap enough for most rural, poor populations to afford them and to be competitive with older antimalarials like chloroquine. 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).⁵ The AMFm launched in early 2011 as a pilot in 8

⁴ACT 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.

⁵It 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

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.

2.3 Malaria Diagnostic Testing

There are two types of diagnostic tests for malaria: microscopy and rapid diagnostic tests. Blood slide microscopy is the most common method used, but it can only be performed in clinics with an equipped lab and electricity. The quality of microscopic diagnosis of malaria can vary greatly depending on the experience and training of the lab technician who prepares, stains and reads the blood slide. The quality of microscopic tests also depends on 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.⁶ The Kenya study cited above found that nearly 80 percent of patients who tested negative for malaria were prescribed antimalarials regardless. This 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).

Rapid diagnostic tests (RDTs) were developed relatively recently to enable malaria testing in remote areas where microscopy is not available. RDTs 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. 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).

2.4 Health Providers and Health Treatment Seeking in Rural Kenya

To provide context for our theoretical framework and experimental design, this subsection provides some descriptive evidence on health care choices that are available to households in

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.

⁶The 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).

rural Kenya and presents some key baseline facts about treatment-seeking behavior in our study population.

As in many developing countries, the range of health care providers in Kenya is vast. Public health facilities vary from small “dispensaries”, which provide very basic outpatient care for the most common types of illness, to hospitals with medical specialists and surgical capacity (Luoma 2010). As in other countries (Leonard 2007; Das et al. 2008), the level of practitioner training and expertise varies widely across Kenyan health facilities, even within the same tier of care. However, in rural areas, patients generally only have access to lower level facilities, as the distance and transport costs to higher level facilities in district centers and urban areas are often prohibitive. 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 (Kangwana et al. 2009; Chaudhury et al. 2006). Rural health facilities typically do not have 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. ACTs are free in public health facilities in Kenya, but are quite often stocked out (Kangwana et al. 2009). Even with free medication, 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.

Households also have the option of treating an illness with over-the-counter medication purchased at a drug shop.⁷ 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 remote areas, whereas the average household in our sample lived more than 6.5 kilometers 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). Private sector supply chains for pharmaceuticals are also more reliable than in the public sector, so drug shops are less often stocked out of medication than health facilities.⁸ The main drawbacks to treating malaria at a drug shop rather than a public health facility is the

⁷Another option is to seek care in the formal private sector (at a clinic or doctor’s office, for example). The cost of this type of care is prohibitively high for our study population, however. At endline, just 4 percent of all illness episodes were treated in the formal private sector.

⁸Indeed, it is often the case that health facilities will send patients to drug shops to purchase the medicines that they are stocked out of. We see some evidence of this in our baseline. When a presumed malaria episode was first treated at the health center, the household reported obtaining drugs from the drug shop 11 percent of the time.

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.

We conclude this section with some basic statistics on malaria treatment seeking behavior reported in our baseline survey. The results, presented in Table 2, are from self-reported behavior in response to presumed malaria episodes. (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 an episode of malaria in the month before baseline. Yet rates of malaria diagnostic testing were relatively low, with 18 percent of households taking a microscopy test and 3 percent of households taking an RDT in the previous month. 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. The drug shop is the most common source of antimalarial medication, however (probably because some patients seeking care at the health center are given prescriptions that people can choose to fill at the drug shop) – antimalarials are procured from a drug shop 52 percent of the time, and from a health center 44 percent of the time.

At baseline, households in our sample had limited access to effective antimalarials – only 21 percent of presumed malaria episodes were reported to be treated with ACTs. The rate of ACT taking is not much higher in children 13 and younger, even though young children are most at risk of severe morbidity and mortality from malaria. Roughly 35 percent of malaria episodes are treated with older, less effective drugs like amodiaquine and sulfadoxine pyrimethamine. Households spend \$1.68 per malaria episode (the median is substantially lower at \$0.77). In either case, this is a remarkably large sum of money given that the agricultural daily wage in this area is around \$1.5 (Dupas and Robinson 2011). In sum, our baseline data suggest that households have frequent malaria episodes that are often treated at the drug shop with inappropriate medications, despite high out of pocket expenditures. Children are slightly more likely to go to a health center and be treated with ACTs. Literate households are more likely to go to health facilities and more than twice as likely to access ACTs than illiterate households.

3 A Model of Malaria Treatment Seeking Under Uncertainty

This section develops a model of treatment seeking behavior in the environment described above. The goal of the model is to highlight the trade-off inherent to 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. 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. The problem of the social planner is thus to maximize a malaria-treatment objective function (some $f(UT, OT)$), subject to a budget constraint.

Another parameter of interest 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. The goal of this section is to discuss 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: $a = h$
3. Purchase other 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 $V^a(\pi)$. It can be decomposed into:

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

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 .⁹ Note that the utilities and prices may be a function of 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: $V^a(\pi) - V^n(\pi)$ 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

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

In practice, there may be heterogeneity in these valuations in the population. In order to study heterogeneity and to clarify the potential distributional impacts of 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 1, top panel, graphs the value curves for the rich and the poor 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 travelling to the health center (where diagnostic testing is available) is preferred to

⁹We assume that $V^a : \pi \rightarrow \mathbb{R}$ 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.

presumptively buying an ACT at lower and intermediate malaria probabilities. We consider this to be the most plausible scenario, but other configurations are certainly possible.

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 private sector (holding the health center price constant) will decrease both $p_P^s(\pi)$ and $p_N^s(\pi)$. 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 $V^n(\pi)$ after the price reduction.

Figure 1, bottom panel, illustrates the impact of the subsidy policy on behavior of the rich and the poor. 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 or high probabilities, and, if the ACT subsidy is large enough, crowd-out from other options among those with a low malaria probability. For the poor, illness with the highest malaria probabilities are now treated with an ACT. The following proposition formalizes the impact of the subsidy on the policy parameters of interest:

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 OT and UT will increase. By assumption A1, the curves $V^s(\pi)$ and $V^n(\pi)$ only intersect once, and $V^s(\pi)$ cut $V^n(\pi)$ from below. This implies that all the marginal illnesses induced to take action s instead of n by the subsidy will have lower malaria probabilities than those illness that would have received ACTs in either case. 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. ■

In other words, 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 worse. However, when there is heterogeneity in valuations in the population, the targeting result may no longer hold. Suppose a fraction γ of the population is rich and fraction $(1 - \gamma)$ is poor:

Proposition 2 *Suppose the subsidy policy changes policy parameters from OT_i , UT_i , and T_i to OT'_i , UT'_i , and T'_i for $i \in \{rich, poor\}$. Furthermore, assume that $T'_{poor} > T_{rich}$. Then it is possible that targeting in the entire population increases due to the subsidy policy: $T' > T$.*

Proof. It suffices to provide an example. Suppose the poor never take ACTs in the absence of the subsidy. Then targeting in the entire population is just $T = T_{rich}$. After the subsidy, targeting in the entire population is given by $\omega' T'_{rich} + (1 - \omega') T'_{poor}$, where $\omega' = \frac{\gamma[\Pi(1-UT'_{rich})+(1-\Pi)OT'_{rich}]}{\gamma[\Pi(1-UT'_{rich})+(1-\Pi)OT'_{rich}]+(1-\gamma)[\Pi(1-UT'_{poor})+(1-\Pi)OT'_{poor}]}$ is the fraction of ACT takers from rich households after the subsidy. Then $T' - T = T'_{poor} - T_{rich} - \omega' (T'_{poor} - T'_{rich})$. For targeting to increase, it therefore must be the case that $\omega' < \frac{T'_{poor} - T_{rich}}{T'_{poor} - T'_{rich}} \leq 1$, where the last inequality follows from Proposition 1. It is clear that $\omega' = 1$ when $\gamma = 1$, and that $\omega' \rightarrow 0$ continuously as $\gamma \rightarrow 0$, which implies $\exists \gamma^*$ such that $T' - T > 0 \forall \gamma < \gamma^*$. ■

In other words, if the subsidy policy crowds in enough high-positivity poor relative to low-positivity 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 a cost of p_R , an individual can take a 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 appropriate medication earlier: this will increase $U_N^s(\pi) - p_N^s(\pi)$.

Both of these effects are captured by writing $\widehat{V}_N^s(\pi) \geq V_N^s(\pi)$, where $\widehat{V}_N^s(\pi)$ is the value of seeking care at the drug shop conditional on not having malaria *and* seeing the negative RDT test result (note that we exclude the cost of taking the RDT, p_R , from $\widehat{V}_N^s(\pi)$). This gives us our third result:

Proposition 3 *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: $V^s(\pi) \geq \max\{V^h(\pi), V^w(\pi)\}$. These individuals will continue to seek care from the drug shop and will choose to use an RDT if:

$$\begin{aligned} \pi V_P^s(\pi) + (1 - \pi) \widehat{V}_N^s(\pi) - p_R &\geq \pi V_P^s(\pi) + (1 - \pi) V_N^s(\pi) \\ (1 - \pi) \left[\widehat{V}_N^s(\pi) - V_N^s(\pi) \right] &\geq p_R \end{aligned} \quad (2)$$

that is, they will use the 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 (that is, for whom $V^s(\pi) < \max\{V^h(\pi), V^n(\pi)\}$) but becomes so once the RDT subsidy is introduced: $\widehat{V}^s(\pi) - p_R \geq \max\{V^h(\pi), V^w(\pi)\}$. 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 . ■

The discussion above assumes perfect compliance with test results at both the health center and the drug shop. Suppose compliance at the health center is partial, so some

individuals who test malaria negative are still given ACTs. Propositions 1 and 2 will go through, since health center crowd out still increases OT while leaving UT unchanged. Now consider partial compliance with the RDT result. 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.

3.4 Summary

The impacts of ACT and RDT subsidies on ACT targeting and crowd out are theoretically ambiguous. They 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. 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 2009.¹⁰ 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. Daily agricultural wages are estimated at approximately \$1.50 (Dupas and Robinson 2011).

¹⁰The 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.

We selected four drug shops, in four rural market centers.¹¹ 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.¹² 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. The vouchers stated the drug shop at 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. An image of an ACT voucher with English translation is in Appendix Figure A1. RDT vouchers were similar in appearance. 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 2. 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 outside a few health facilities.¹³ 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. The 92 percent subsidy level (Ksh 40 for an adult dose) corresponds to the Kenyan government’s target retail price under the AMFm. The lower subsidy amounts reflect prices that could be realized if less of the subsidy were passed through the supply chain, or if the subsidy amount were reduced, potentially to fund RDTs.¹⁴ The third group received vouchers for both subsidized ACTs and RDTs, with households also randomized into one of three RDT subsidy levels. The most expensive RDTs were subsidized

¹¹Participating 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.

¹²In rare cases when there was no female head or she was not available, we interviewed the male head of household. The ACT used in this study was Coartem (Artemether Lumefantrine), produced by Novartis Pharmaceuticals. The RDT was the ICT Malaria Pf test, produced by ICT Diagnostics. This type of test only detects the *P. falciparum* strain of malaria, which accounts for 98 percent of all malaria infections in Kenya and is by far the most deadly strain of malaria (Kenya Division of Malaria Control 2011).

¹³The 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.

¹⁴This 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.

by 85 percent, corresponding to a retail price of roughly \$0.20.¹⁵

Since ACTs are priced by dose, with the appropriate dose determined by age, the four ACT subsidy levels (0, 80, 88 and 92 percent) differed in the “price-per-pill” to which a household was entitled. Figure A2 in the Appendix demonstrates the pricing and dosing regimens in the study.¹⁶ The randomization of households was done using a computerized random number assignment algorithm and was stratified by drug shop, by the household’s distance to the drug shop (in quartiles) and by the presence of children in the household.

As discussed in the previous section, the success of a subsidy policy depends upon the fraction of malaria positive people who do not receive an ACT under the policy (*UT*) and the fraction of malaria negative people taking ACTs under the policy (*OT*). To estimate these policy parameters, a sub-sample of households in all the treatment groups other than the no subsidy group was randomly selected to get a “surprise RDT”.¹⁷ 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 given at the drug shop 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. No one was selected for a surprise RDT in the no subsidy group because we anticipated very low take-up of the ACT in this group. (Indeed, only 8 households redeemed an ACT voucher in this group).

At the end of the experiment we visited households again to administer an endline survey. Only 5 percent of households surveyed at baseline were not reached at endline, and attrition was balanced across treatment arms. After the endline survey we informed households that their vouchers had expired, and we collected unused vouchers back from households.¹⁸

¹⁵Some 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. For additional detail on the separate RDT treatments, see Cohen et al. (2010).

¹⁶Ideal 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.

¹⁷49 percent of households not offered an RDT, 71 percent of households offered an RDT for Ksh 15, and 100 percent of households offered a free RDT were selected for surprise testing.

¹⁸As compensation, all households were given a tin of cooking fat at endline regardless of whether or not they returned any vouchers to us.

4.2 Data

We use two types of data in the analysis that follows. The first is the administrative data based on redemptions at the drug shop, and the second is survey data from baseline and endline surveys administered at the beginning and end of the study.

The administrative data captures the details of the drug shop transaction (including medicines bought, symptoms, patient characteristics, and true malaria status in case an RDT was administered). This data was recorded by trained enumerators posted at each of the four participating drug shops during opening hours, every single day throughout the study period. This data includes information on over 1,700 drug shop visits made by study households over a four-month period.

The endline survey was administered about four months after the vouchers had been distributed. It asked households to recall all illness episodes that involved fever, chills, headache, sweats, nausea, cough, or diarrhea, that the household experienced in the previous four months. 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. One concern is that households in our ACT subsidy treatments would remember significantly more illness episodes, (if the vouchers served to jog their memory or make an illness episode more salient, for example). We do not find any significant evidence of this – Appendix Table A1 shows that there are no systematic differences in illness reporting at endline across treatment groups.

We use these two sources of data in combination. The administrative data is used to explore the impact of subsidies on the uptake of ACTs and RDTs and on the targeting of ACTs to malaria positive people at the drug shop. In particular, we use voucher redemption data to measure the demand for ACTs and RDTs at the drug shop. Furthermore, we use the subsample of households selected for a surprise RDT to tell us what fraction of ACT buyers at the drug shop are truly malaria positive.

In order to gauge the overall impact of the ACT and RDT subsidies on uptake and targeting, however, we have to know how our sample treated all illnesses, not just those treated at the drug shop. The endline data allows us to estimate the impact of the subsidies on ACT and RDT uptake for all illness episodes, regardless of where they were treated, but the endline data alone is not informative about the issue of targeting. To truly measure targeting, we would need data on the true malaria status of each illness treated by our households throughout the study, regardless of treatment channel. While we cannot observe actual positivity, we can proxy for it based on reported symptoms, which we collected for all illness episodes reported at endline and all illness treated at the drug shop. Because it also includes malaria status (based on an RDT test result) for over 1,300 presumed malaria

episodes, the administrative data enables us to estimate the relationship between reported symptoms and malaria positivity. We can then use these estimates to impute malaria positivity to our endline illness episodes. The next subsection provides additional detail on this procedure.

4.3 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. 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 (an “adult”). 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.¹⁹

The results of this regression are presented in Table 3. 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 3 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 A3 illustrates the strength of this relationship graphically by

¹⁹We 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.

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. On the other hand, our results are for a selected sample of episodes that households suspected to be malaria and therefore chose to treat at the drug shop. In this case, it is not obvious that an age gradient should be apparent. The presence of the age gradient suggests that households are less adept at identifying malaria in older individuals, possibly because the symptoms are less severe and overlap with other milder diseases, such as cold and flu.

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. However, 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. The 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 measure 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.

4.4 Baseline Characteristics of Study Sample

In Table 1 we present basic 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.

4.5 Status Quo Treatment-Seeking Behavior

As highlighted by the model, the impact of the two subsidy regimes under study will depend on the relative value of the three possible malaria treatment-seeking behaviors (buying ACTs at the drug shop, going to the health center, other) across malaria risk levels. To get a sense of how these three options compare in the absence of a subsidy, Figure 3 plots the frequency of these three possible actions by predicted positivity among the control group. The figure graphs results of local linear regressions of the following form:

$$y_{eh} = g(predpos_{eh}) + \varepsilon_{eh} \quad (3)$$

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.²⁰

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 store slopes upwards only in the top two tertiles of the malaria positivity distribution.²¹ 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

²⁰We 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.

²¹We will separately study the three components of the “other” category – seeking no care (28 percent of the cases), taking a substandard antimalarial or antipyretic from the drug shop (51 percent of the cases), and taking another medication (21 percent of the cases) – in subsequent analysis.

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 1. 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 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 will 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 panel B of Figure 1. The fact that low SES households overwhelmingly 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. Even though treatment at the health center is free, the health center is on average 6.6 kilometers away as the crow flies (compared to 1.7 km away for the drug shop). Reaching the health center might therefore require taking costly public transportation, or walking for 1 to 2 hours, something that might be difficult during an illness episode. 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), this could have attractive implications in terms of both ACT access and targeting.

5 Results

5.1 Comparing Drug Shop Subsidy Regimes with the Status Quo

We first study whether the two different treatment regimes – ACT subsidy only and ACT+RDT subsidy – significantly impact households’ treatment seeking behavior *vis-à-vis* the status quo (no retail sector subsidy). 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 sin-

gle group.²² (In subsection 5.2 we will examine the sensitivity of the impacts to the subsidy level).

We begin by studying how the subsidy impacts the three treatment-seeking behaviors featured in the model. We then further unpack our results by studying provider choice, use of diagnostic tests, and medication choice in turn. Figure 4 presents the results of treatment-group specific local linear regressions specified by equation 3. Panel A illustrates results separately for each of the three treatment-seeking behaviors: buying ACTs at the drug shop, visiting the health center, and doing something else. We present evidence of the impacts for the full sample in panel A. Since literate and illiterate households exhibit very different behavior under the status quo, and the theory suggests that they could be impacted differently by the subsidies, we present evidence of the impact of the two subsidy regimes separately by literacy status in panels B and C. Since households were only given two ACT vouchers and (when relevant) two RDT vouchers, 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.²³ We also exclude all ACT-only households who were randomly selected for a surprise RDT test from the endline data analysis, as the surprise test could impact their medication choice. We do *not* exclude surprise tested households who received RDT vouchers.²⁴

The first row of graphs in Figure 4 shows that both subsidy regimes led to an increase in the likelihood that households buy an ACT at the drug shop across the entire range of predicted positivity. The uniform increase masks different crowd out patterns by predicted positivity, however. In particular, crowd out of the health center is largely concentrated in the upper two tertiles of predicted positivity, while crowd out of no or sub-therapeutic care occurs across all ranges of predicted positivity. (Our subsequent analysis will show that this pattern captures two different types of crowdout – doing nothing at low malaria probabilities, versus purchasing a substandard malaria treatment at higher malaria probabilities).

Panels B and C show that the effects of the subsidy regime are very different across

²²The mix of subsidized ACT prices in the “no RDT subsidy” and “RDT subsidy” treatment groups are slightly different. As such, any differential effects due to the different price mixes will load onto the “RDT subsidy” dummy. However, results for the RDT treatment are nearly identical if we separately dummy out ACT prices and constrain the RDT treatment effect to be constant across subsidized ACT price levels. We therefore present the pooled results for ease of interpretation.

²³Some 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.

²⁴Eighty 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.

literacy groups. All the crowd-out for illiterate households is from no or sub-therapeutic care. For literate households, there is important crowd out of the health center for the middle and upper tertiles of positivity, and crowd out of no/subtherapeutic care in the lower tertile. This is broadly consistent with our theoretical framework, as sketched in Figure 1.

In what follows, we analyze the impacts of the subsidy regimes on treatment-seeking behavior in more detail. To do so, we divide treatment seeking into three domains: (a) provider choice (where to seek treatment) (b) use of diagnostic testing, and (c) drug choice. In the next subsection, we then go on to study how ACT price variation *within* a range of subsidized prices impacts ACT demand and targeting.

Impacts on Provider Choice Table 4 estimates the effects of the subsidy regimes on health provider choice. The first panel examines overall mean effects of the different subsidy regimes by presenting results from the following regression:

$$y_{eh} = \delta + \alpha ACTsub_h + \beta RDTsub_h + age'_h\gamma + \lambda_{strata} + \varepsilon_{eh} \quad (4)$$

where y_{eh} is the outcome of interest for illness episode e in household h (seeking care at the drug shop, seeking care at the health center, or not seeking care). $ACTsub_h$ is a dummy variable equal to 1 if the household was randomly selected to receive an ACT subsidy, $RDTsub_h$ is a dummy variable equal to 1 if a household was randomly selected to receive an RDT subsidy, age_h is a vector controlling for the household head’s age, and λ_{strata} are strata fixed effects.²⁵ Since all households sampled for an RDT subsidy also received an ACT subsidy, the coefficient α gives the difference between the ACT only treatment group and the control, while β gives the difference between the ACT only subsidy group and the ACT+RDT subsidy group.

The first three columns 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 of households not seeking any care decreased by 9 percentage points (41 percent) in both subsidy treatment groups. These effects are significant at conventional levels (though only marginally so for the health center). 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

²⁵As mentioned earlier, we control for household head’s age because the age composition of control households is tilted more towards adults, as illustrated by Table 1. When head age is missing we recode it to the mean and separately dummy these observations out.

the health center, as we had hypothesized given baseline treatment-seeking behaviors. Our estimates of β illustrate that provider choice patterns in the ACT and ACT+RDT treatment groups were essentially identical. This suggests that RDTs had a limited extensive margin effect (they do not draw more illness episodes to the drug shop). We therefore expect that any targeting effects of RDTs will be driven primarily by changes in medication taking among households who would have come to the drug shop anyway (i.e. the intensive margin).

The second panel of Table 4 examines impacts of the subsidy treatments by tertile of predicted malaria positivity. That is, we report results from the following regression:

$$y_{eh} = \delta_0 + \sum_{j=1}^3 (\alpha_j ACTsub_h \times tert_{jeh} + \beta_j RDTsub_h \times tert_{jeh} + \delta_j tert_{jeh}) + age'_h \gamma + \lambda_{strata} + \varepsilon_{eh} \quad (5)$$

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 The first three columns in this panel illustrate that 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 can only reject that crowd-out patterns are the same across tertiles for “sought no care”).

These impacts are largely concentrated among literate-headed households – this observation, coupled with the increase in ACT purchases by illiterate-headed households observed in Figure 4, suggests that illiterate-headed households may not have substantially changed where they went, but may have substantially changed what they *bought*. A notable exception is that we estimate that the ACT and ACT+RDT subsidy treatments significantly increase rates of seeking no care for the middle tertile of illiterate-headed households. However, this result is most likely aberration – the control group in the middle tertile cell is relatively small, and the estimates are not robust to recalculating positivity tertiles within the subset of illness episodes among illiterate-headed households.

Impacts on Access to Diagnostic Testing The ACT subsidies clearly draw additional households to the drug shop, sometimes at the expense of the health center. A primary concern with this particular form of crowd out is that it could reduce access to diagnostic services. Figure 5 and Table 5 conduct analyses analogous to those just discussed, but

²⁶Note that although the tertile dummies are generated regressors, the null hypothesis of interest specifies that their coefficients are equal to zero. In this case, traditional standard errors are consistent (Newey and McFadden 1994).

with indicators of malaria testing as outcomes of interest. Panel A of Figure 5 graphs how reported rates of RDT testing, microscopy testing, and the superset, “any malaria test”, vary with treatment group and predicted malaria positivity. The ACT+RDT subsidy significantly increased rates of RDT taking. Furthermore, we find no evidence of crowd out of microscopy overall, despite health center crowd out. (Although microscopy results in Panels B and C of Figure 5 suggest some impacts of the treatments on rates of microscopy testing, our analysis by positivity tertile in Table 5 finds no significant impacts.) Overall, the ACT+RDT subsidy regime nearly doubled 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. As mentioned earlier, over 80 percent of the ACT+RDT treatment households 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.²⁷

Impacts on Medication Choice Finally, we study the impact of the subsidy regimes on access to ACTs and other medications. Figure 6 presents local linear regression results for whether or not an illness was: (1) treated with an ACT, (2) treated with some other ineffective antimalarial or an antipyretic (which could improve symptoms but not clear the malaria infection), or (3) treated with an antibiotic. Table 6 presents the analogous regression analysis. Overall, both subsidy regimes increase access to ACTs by almost 60 percent. The results by literacy reveal desirable distributional properties of the subsidy. As shown in Figure 6, in the absence of any subsidy literate-headed households are substantially more likely to take an ACT at all levels of malaria positivity (they take ACTs for 36.5 percent of illness episodes as compared to 10.8 percent of episodes in illiterate-headed households). This access gap considerably decreases with subsidies – the coverage rates become 44.6 percent and 38.0 percent, respectively.

Another result apparent in Figure 6 and Table 6 is that the subsidy regimes crowded

²⁷Table 5 also reveals some evidence that exposure to the ACT-only subsidy increased rates of RDT test taking for illiterate households. This could be due to the fact that, at each study drug shop, we had to make RDTs available for general purchase at cost (Ksh 50, or \$0.64) so as not to deny any households access to diagnostics if they had not received an RDT voucher but had heard about tests being performed at the drug shop and asked for one. We did not advertise for this, but nevertheless some households coming to the study drug shop to redeem ACT vouchers asked to purchase an RDT at the general price.

out the use of less effective malaria therapies and antibiotics at higher levels of predicted positivity among literate-headed households. In the upper tertile of predicted positivity, the subsidy treatments decreased these households' use of substandard malaria therapies by 28-29 percentage points and antibiotics by 19-20 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.)

The RDT subsidy add-on did not significantly change rates of ACT taking in any of the predicted positivity tertiles. However, there is some marginal evidence that RDTs actually *increased* use of antibiotics in the lowest tertile of malaria positivity. This suggests that some individuals may have still taken an ACT just to be safe, but also took other medication in case they were indeed malaria negative.

Summary of Results So Far To summarize, our results comparing the subsidy treatments to the control imply that:

- Both subsidies increased treatment seeking at the drug shop. No-care was crowded out at the lowest malaria positivity tertile, while the health center was crowded out in the middle tertile.
- The add-on RDT subsidy significantly increased access to diagnostics for malaria, doubling the share of illness episodes that received a malaria test. The ACT-only subsidy did not significantly reduce access to microscopy.
- Both subsidy regimes significantly increase access to ACTs. The gain is particularly pronounced among illiterate-headed households, who had the lowest rates of access in the control group

These results show that both types of subsidy regimes (ACT-only and ACT+RDT) represent a substantial improvement versus the status quo. However, these results are not informative about differences in outcomes between different subsidy levels. Understanding how outcomes vary with the size of the subsidy is important for two reasons: First, the final retail price of

ACTs is uncertain under the AMFm. If access falls sharply as the retail price creeps up from the official target price, a larger subsidy may be warranted. Second, an important policy alternative to the AMFm would be to divert some of the ACT subsidy to subsidies for RDTs. The attractiveness of this alternative will depend both on the price elasticity of demand for ACTs across a range of subsidized prices, as well as the benefits of RDTs in terms of improving targeting and access to illness-appropriate treatment. The next subsection investigates these issues by exploiting the within-subsidy price variation in our experimental design.

5.2 Comparing Drug Shop Subsidy Levels with Each Other

Improving Allocative Efficiency through ACT Prices We begin by studying how different ACT subsidy levels impact targeting and access. In particular, 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 estimating how different subsidy levels impact targeting.

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. These results shed light on the impact of price variation on ACT demand *within the private 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 (again, excluding those households who received no RDT voucher but were selected for surprise testing).

Table 7 presents our price-elasticity results based on both the administrative drug shop data and the endline data. 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:

$$y_h = \beta_0 + \beta_1 ACT88_h + \beta_2 ACT80_h + \beta_3 ACT92 \times RDT_h + \beta_4 ACT88 \times RDT_h + \beta_5 ACT80 \times RDT_h + age'_h \gamma + \lambda_{strata} + \varepsilon_h \quad (6)$$

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. The table presents results for three 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). We also present results of a specification where we constrain the impact of ACT price (in USD) on outcomes to be linear:

$$y_h = \beta_0 + \beta_1 ACTprice_h + \beta_2 RDT_h + \beta_3 ACTprice \times RDT_h + age'_h \gamma + \lambda_{strata} + \varepsilon_h \quad (7)$$

The first column of Table 7 reveals minimal impacts of higher ACT prices on ACT access 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 is considerably lower than the price elasticity of the demand for malaria-preventing bednets estimated by Cohen and Dupas (2010) in the same area of Kenya. This very low price-elasticity over the subsidy range is observed among both illiterate and literate households, as shown in Figure 8.

A comparison of columns 2 and 3 of Table 7 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, 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

²⁸This 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.

²⁹One 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 in post at the drug shop throughout the study period

The analysis based on the endline data presented in columns 4-6 of Table 7, 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.

Table 8 studies targeting directly, again making use of both our administrative and endline data. The first five columns of Table 8 study targeting at the drug shop. The first column studies selection by running regressions of the same forms specified by equations 6 and 7, with “sought treatment” (i.e. coming to the drug shop to redeem either an ACT or, when relevant, an RDT voucher) as an outcome. Here, we observe limited selection effects, none of which are significantly different from zero.

The next two columns study selection in terms of malaria positivity by limiting the sample to treatment seekers selected for a surprise RDT.³⁰ For a subset of households (those sampled for a surprise RDT), we know their true malaria status, and can directly regress their malaria status on the subsidy levels (column 2). In column 3, we use the same sample of households and regress predicted malaria positivity (based on age and symptoms) on the subsidy levels. 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 19 percentage points more likely to test positive as compared to 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 Table 7. 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 3) are similar to those obtained using actual positivity, but the coefficients are substantially lower – this is consistent with our analysis in the Appendix, where we show that using predicted positivity will likely result in coefficients with a downward bias. When we limit the analysis to ACT takers, our targeting results for the ACT-only treatments (columns 4 and 5 of Table 8) are virtually unchanged. This is to be expected, as only one household in the 92-percent-ACT-subsidy-only treatment group sought treatment

were instructed to never sell 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.

³⁰When the sample is limited to treatment seekers or ACT takers, we omit strata and age controls so as not to absorb selection effects. Our three subsidy price treatment groups are balanced in terms of age of the household head and other demographics.

but did not redeem an ACT voucher.³¹

The final three columns repeat the analysis using our endline sample of first illness episodes. Here we define “sought treatment” to be equal to one if the household reports that an illness episode was treated with an ACT or a malaria test of any kind. Point estimates suggest that higher prices increase positivity among ACT takers, though estimates are not significantly different from zero. However, our results are similar to the administrative results using predicted positivity – this suggests our initial results using actual positivity in the surprise tested population may be an accurate assessment of overall targeting impacts.

Improving Allocative Efficiency through Diagnostics Access 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).

Somewhat surprisingly, the analysis in Tables 7 and 8 does not reveal many significant impacts of RDTs on ACT demand and targeting. First, as shown by the results in the first column of Table 8, households who were given RDT vouchers were only very slightly more likely to seek treatment at the drug shop, and insignificantly so. Second, there is no clear pattern in how the RDT subsidy interacts with the ACT subsidy level: when combined with the highest ACT subsidy level, RDT provision appears to select in individuals who are *more* likely to be malaria positive, whereas at lower subsidy levels, RDTs select individuals who are *less* likely to be malaria positive (Table 8, columns 2 and 3). There is no compelling theoretical explanation for this asymmetry, so we choose to interpret the positive targeting impact of the RDT subsidy observed in the redemption data with caution. 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

³¹This is because the household was given an RDT voucher by mistake. This type of mix-up happened very rarely (≈ 1 percent of the sample), but when it did occur, we recorded households under the originally intended treatment group.

around 6 percentage points, rather than 18 percentage points.

Summary Figure 7 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), high (92 percent) ACT subsidy-no RDT, low (80 percent) ACT subsidy-no RDT, and low ACT subsidy-RDT. Overall, the low 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-no RDT 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 – our estimates using actual positivity among drug shop clients imply the targeting benefit would be around 24 percentage points. 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

6.1 Methodology

In order to assess the benefits of the different subsidy regimes, we construct estimates of the three policy parameters outlined in Section 3:

- UT : The share of malaria episodes that are not treated with ACTs
- OT : The share of non-malaria episodes that are treated with ACTs
- T : The share of ACT takers who actually have malaria

These parameters assess how well the subsidy regimes perform in terms of access (making sure malaria positive patients get ACTs) and targeting (minimizing the number of malaria negative patients taking ACTs). However, the subsidy optimization problem is subject to a budget constraint, so we also calculate the following measures of subsidy cost:

- The subsidy cost per malaria episode – this captures overall program costs

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

We make use of our endline data and predicted positivity estimates to calculate the metrics above. Specifically, among the first illness episode sample, we run regressions of the form specified by equation 7, where 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).³²

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. 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.

6.2 Cost Effectiveness Results

Table 9 presents results of our cost effectiveness calculations. Panel A reveals results that are, unsurprisingly, consistent with our earlier targeting and demand results. Most regimes perform comparably in terms of UT , although somewhat surprisingly the ACT 92, no RDT

³²As illustrated by Figure A2, 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.

regime performs worst, while the ACT 92+RDT regime performs best. The driver of this result can be found in Table 7 – ACT taking is highest among adults and lowest among children in the high subsidy-no RDT regime, while highest among children and lower among adults once RDTs are provided.

The results for policy parameter OT reveal that both price and RDTs are effective tools for limiting overtreatment. Here, RDTs appear to be most valuable at higher ACT subsidy levels. This is intuitive – absent diagnostics lower ACT prices will select more “marginal” illnesses that are less likely to be malaria. When RDTs are sufficiently low cost to be attractive to these marginal cases, the test has the potential to provide a great deal of screening value.

We also note that comparing changes in UT and OT across regimes conforms to our theoretical predictions regarding RDTs. The introduction of RDTs reduces both UT and OT , so T consequently increases (this is Proposition 3). Although UT increases slightly with price across the ACT+RDT regimes (as predicted by Proposition 1), the measure is essentially flat in the ACT-only regimes – this is largely driven by the very low price elasticity of demand across the range of subsidies that we consider. Taken together, the results in columns 1-3 suggest that a slight increase in the subsidized price of ACTs could have beneficial targeting impacts while not harming ACT access. However, these results do *not* imply that a subsidy is unwarranted – the stark differences in access between our subsidy group and the control group presented in Table 6 make this very clear.

Should this saved subsidy money be shifted to RDTs? The RDT regimes perform better in terms of targeting, but RDTs are also costly, as reflected by columns 4 and 5 of Table 9. In particular, the 80 percent ACT subsidy with no RDTs performs just as well in terms of UT , OT , and T as compared to the same subsidy level plus RDTs, 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. 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 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. 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. 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 9, where we assume tested individuals only take ACTs when the RDT is positive.

Calculations for *OT* 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. Indeed, we find that illnesses least likely to be malaria were more likely to be treated with an antibiotic in the ACT+RDT treatment group. 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 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 three 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. Furthermore, we find evidence that price is a useful tool for selection – slightly higher ACT prices reduce ACT taking among adults, who are substantially less likely to be malaria positive, while leaving access among children unchanged. Second, we find that overdiagnosis of malaria is extremely common; therefore large ACT subsidies alone would lead to an important increase in inappropriate use of ACTs. Third, we find that demand for rapid diagnostic testing is extremely high when it is readily affordable and available.

Our results also generate a number of important questions for future research. The first obvious question 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 2009). In a companion paper (Cohen, Dupas, and Schaner 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.

The second question is 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. 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.

More generally, many questions regarding the supply side of the subsidy policy remain unanswered. The results of our study of the demand side suggest that bundling the currently proposed ACT subsidy with a subsidy for rapid diagnostic testing could further the goal of reducing the burden of malaria not only today, but also tomorrow. However, additional research is needed to determine how to best implement the subsidy policy to ensure that donor dollars are passed on to consumers, and that both drugs and tests are used properly while remaining widely available.

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A Predicted Positivity and Regression Bias

Here we illustrate the downward bias inherent in using predicted malaria positivity to assess targeting impacts. 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* : $E[\hat{\pi}_{eh}] = \tilde{\pi}_{eh}$.
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:

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

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:

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

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

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

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 $\Omega\gamma(1 - \Pi_1^1) + (1 - \Omega)(1 - \Pi_1^0)$ of the negative episodes they will take an ACT. So, the share of ACT takers who are malaria positive in the treatment and control groups can be written as

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

where $\psi = \frac{\Omega(\Pi_1^1 + \gamma(1 - \Pi_1^1))}{\Omega(\Pi_1^1 + \gamma(1 - \Pi_1^1)) + (1 - \Omega)}$ 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:

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

Which approaches $(1 - \Pi_0)$ when $\gamma \rightarrow 0$ and $\Omega \rightarrow 1$. However, if we can only measure *predicted* positivity, we will get:

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

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

$E[\tilde{\pi} | RDT = 1, ACT = 1]$ into contributions from the tested and untested groups:

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

Again, by assumption 1, the untested population poses no problems:

$E[\tilde{\pi} | RDT = 1, ACT = 1, test = 0] = S_1^0$. 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).

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

Now, by assumption 3

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

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

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

putting all of this together

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

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

Specifically:

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

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:

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

Table 1: Summary Statistics

<i>Characteristics of Interviewed Household Head</i>									
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		
<i>Household Characteristics</i>									
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		
<i>Baseline Malaria Knowledge and Health Practices</i>									
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 month	1.20	1.20	1.23	0.985	0.744	0.508	2789		
<i>Cost Per Episode (Among Those Seeking Any care)</i>									
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: Baseline Treatment Seeking Behavior

	By Household SES			By Patient's Age		
	All	Illiterate	Literate	Patient 13 or Younger	Patient 14 or Older	p-value Child=Adult
Household Level Malaria and Diagnostic Incidence						
Number of presumed malaria episodes last month	1.22	1.36	0.994	0.617	0.568	-
At least one presumed malaria episode last month	0.685	0.739	0.600	0.435	0.387	-
Household member took RDT test (in last month)	0.029	0.034	0.023	-	-	-
Household member took microscopy test (in last month)	0.180	0.209	0.133	-	-	-
Treatment Seeking for All Presumed Malaria Episodes						
Did not seek care	0.182	0.260	0.147	0.139	0.218	0.000***
Went to health center	0.413	0.331	0.448	0.470	0.364	0.000***
Went to drug shop	0.369	0.354	0.376	0.357	0.382	0.159
Medication for All Presumed Malaria Episodes						
No antimalarial taken	0.221	0.302	0.186	0.184	0.252	0.000***
Took ACT	0.213	0.120	0.255	0.240	0.193	0.002***
Took Sulfadoxine-Pyrimethamine (SP)	0.100	0.074	0.112	0.075	0.130	0.000***
Took Amodiaquine (AQ)	0.181	0.166	0.187	0.212	0.153	0.000***
Took Other Antimalarial	0.072	0.055	0.079	0.095	0.050	0.000***
Forgot Name of Antimalarial Taken	0.217	0.285	0.185	0.198	0.225	0.089*
Source of Antimalarials (Among Antimalarial Takers)						
Health Center	0.444	0.413	0.454	0.475	0.416	0.005***
Drug Shop	0.523	0.540	0.518	0.498	0.552	0.011**
Another Source	0.033	0.048	0.028	0.027	0.032	0.414
Cost Per Episode (Among Antimalarial Takers)						
Total Cost (\$US)	1.68	1.38	1.80	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.

Table 3: 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) × Cough	0.017	(0.062)
(Age 14 or Above) × Chills	-0.051	(0.074)
(Age 14 or Above) × Headache	0.016	(0.065)
(Age 14 or Above) × Diarrhea	0.057	(0.093)
(Age 14 or Above) × Runny Nose	-0.365	(0.240)
(Age 14 or Above) × Vomiting	0.074	(0.051)
(Age 14 or Above) × Body Pain	-0.168	(0.131)
(Age 14 or Above) × Malaise	0.055	(0.091)
(Age 14 or Above) × Poor Appetite	0.052	(0.075)
(Age 14 or Above) × Age	-0.094***	(0.018)
(Age 14 or Above) × 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 levels respectively.

Table 4: Impact of ACT and RDT 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	
<i>Specification 1 – Main Effect</i>												
α	0.159*** (0.047)	-0.076* (0.043)	-0.091*** (0.036)	0.072 (0.074)	0.002 (0.056)	-0.096 (0.061)	0.215*** (0.061)	-0.135** (0.059)	-0.085** (0.043)			
β	0.000 (0.027)	-0.006 (0.023)	0.006 (0.018)	-0.031 (0.046)	0.034 (0.036)	0.013 (0.036)	0.018 (0.033)	-0.025 (0.030)	0.001 (0.021)			
p-val for F-Test $\alpha + \beta = 0$	0.000***	0.042**	0.010***	0.530	0.468	0.138	0.000***	0.003***	0.037**			
<i>Specification 2 – Impact by Predicted Probability</i>												
α_1	0.195*** (0.071)	-0.021 (0.060)	-0.186*** (0.062)	0.054 (0.109)	0.080 (0.077)	-0.153 (0.101)	0.298*** (0.097)	-0.088 (0.088)	-0.221*** (0.078)			
α_2	0.171** (0.083)	-0.182*** (0.075)	0.010 (0.054)	0.091 (0.165)	-0.213 (0.147)	0.124** (0.060)	0.201** (0.096)	-0.180** (0.088)	-0.024 (0.069)			
α_3	0.072 (0.089)	-0.047 (0.088)	-0.040 (0.047)	0.023 (0.119)	0.027 (0.088)	-0.097 (0.087)	0.120 (0.129)	-0.142 (0.130)	0.021 (0.048)			
β_1	-0.009 (0.045)	-0.012 (0.037)	0.024 (0.034)	0.056 (0.070)	-0.010 (0.056)	-0.028 (0.060)	-0.064 (0.060)	-0.012 (0.052)	0.072* (0.042)			
β_2	-0.026 (0.046)	0.018 (0.040)	-0.005 (0.033)	-0.142* (0.084)	0.054 (0.067)	0.081 (0.063)	0.036 (0.057)	-0.004 (0.050)	-0.047 (0.039)			
β_3	0.036 (0.043)	-0.024 (0.039)	-0.002 (0.023)	-0.016 (0.083)	0.065 (0.065)	-0.011 (0.053)	0.054 (0.052)	-0.055 (0.050)	-0.002 (0.025)			
p-val: $\alpha_1 + \beta_1 = 0$	0.004***	0.542	0.005***	0.253	0.279	0.043**	0.008***	0.214	0.049**			
p-val: $\alpha_2 + \beta_2 = 0$	0.056*	0.019**	0.920	0.740	0.259	0.000***	0.006***	0.021**	0.245			
p-val: $\alpha_3 + \beta_3 = 0$	0.192	0.397	0.343	0.942	0.246	0.180	0.158	0.111	0.674			
p-val: $\alpha_1 = \alpha_2 = \alpha_3$	0.535	0.217	0.049**	0.944	0.202	0.024**	0.507	0.755	0.030**			
p-val: $\alpha_1 + \beta_1 = \alpha_2 + \beta_2 = \alpha_3 + \beta_3$	0.742	0.304	0.081*	0.620	0.275	0.000***	0.907	0.688	0.129			
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: Robust standard errors in parentheses, clustered at household level. Regressions include first illness episode that occurred after baseline. A few households have more than one first illness episode if two family members were sick simultaneously. All regressions control for household head age and a full set of strata dummies. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 5: Impact of ACT and RDT Subsidy on Diagnosis Seeking, by Literacy and Predicted Malaria Probability

	All						Illiterate			Literate		
	Microscopy		Any Malaria		Test		Microscopy		Any Malaria		Test	
	RDT Test	Test	RDT Test	Test	RDT Test	Test	RDT Test	Test	RDT Test	Test	RDT Test	Test
<i>Specification 1 – Main Effect</i>												
α	0.008 (0.025)	-0.019 (0.033)	-0.011 (0.038)	0.054 (0.034)	-0.005 (0.046)	0.049 (0.056)	-0.005 (0.036)	-0.036 (0.047)	-0.041 (0.053)	0.009 (0.049)	0.009 (0.049)	-0.037 (0.086)
β	0.231*** (0.019)	-0.010 (0.019)	0.221*** (0.024)	0.154*** (0.029)	0.015 (0.027)	0.169*** (0.037)	0.266*** (0.024)	-0.016 (0.025)	0.250*** (0.031)	0.000*** (0.000***)	0.000*** (0.000***)	0.000*** (0.000***)
p-val for F-Test $\alpha + \beta = 0$	0.000***	0.327	0.000***	0.000***	0.820	0.000***	0.000***	0.219	0.000***	0.000***	0.219	0.000***
<i>Specification 2 – Impact by Predicted Probability</i>												
α_1	0.023 (0.030)	-0.017 (0.051)	0.006 (0.057)	0.075* (0.042)	0.037 (0.072)	0.112 (0.082)	0.009 (0.049)	-0.047 (0.075)	-0.037 (0.086)	0.009 (0.049)	0.009 (0.049)	-0.037 (0.086)
α_2	0.012 (0.048)	-0.010 (0.059)	0.002 (0.070)	0.054 (0.043)	-0.082 (0.112)	-0.029 (0.113)	0.009 (0.064)	-0.012 (0.070)	-0.002 (0.087)	0.009 (0.064)	0.009 (0.064)	-0.002 (0.087)
α_3	0.001 (0.058)	-0.031 (0.063)	-0.030 (0.076)	0.016 (0.084)	-0.006 (0.108)	0.010 (0.108)	-0.007 (0.079)	-0.063 (0.102)	-0.071 (0.106)	-0.007 (0.079)	-0.007 (0.079)	-0.071 (0.106)
β_1	0.155*** (0.028)	-0.027 (0.032)	0.128*** (0.040)	0.111*** (0.043)	-0.029 (0.048)	0.082 (0.060)	0.177*** (0.038)	-0.024 (0.042)	0.153*** (0.056)	0.177*** (0.038)	0.177*** (0.038)	0.153*** (0.056)
β_2	0.219*** (0.031)	0.002 (0.033)	0.221*** (0.041)	0.177*** (0.047)	0.018 (0.052)	0.195*** (0.065)	0.237*** (0.039)	0.006 (0.042)	0.243*** (0.050)	0.237*** (0.039)	0.237*** (0.039)	0.243*** (0.050)
β_3	0.292*** (0.036)	-0.001 (0.029)	0.291*** (0.042)	0.216*** (0.065)	0.064* (0.035)	0.279*** (0.072)	0.319*** (0.043)	-0.029 (0.039)	0.289*** (0.052)	0.319*** (0.043)	0.319*** (0.043)	0.289*** (0.052)
p-val: $\alpha_1 + \beta_1 = 0$	0.000***	0.324	0.009***	0.000***	0.906	0.006***	0.000***	0.297	0.144	0.000***	0.000***	0.144
p-val: $\alpha_2 + \beta_2 = 0$	0.000***	0.886	0.001***	0.000***	0.548	0.131	0.000***	0.930	0.003***	0.000***	0.000***	0.003***
p-val: $\alpha_3 + \beta_3 = 0$	0.000***	0.587	0.000***	0.005***	0.384	0.005***	0.000***	0.339	0.028**	0.000***	0.000***	0.028**
p-val: $\alpha_1 = \alpha_2 = \alpha_3$	0.938	0.969	0.923	0.796	0.658	0.525	0.983	0.899	0.879	0.983	0.983	0.879
p-val: $\alpha_1 + \beta_1 = \alpha_2 + \beta_2 = \alpha_3 + \beta_3$	0.178	0.874	0.307	0.681	0.657	0.690	0.395	0.673	0.528	0.395	0.395	0.528
DV Mean (Control Group)	0.068	0.148	0.216	0.031	0.108	0.138	0.094	0.177	0.271	0.094	0.094	0.271
N	2042	2042	2042	705	705	705	1332	1332	1332	1332	1332	1332

Notes: Robust standard errors in parentheses, clustered at household level. Regressions include first illness episode that occurred after baseline. A few households have more than one first illness episode if two family members were sick simultaneously. All regressions control for household head age and a full set of strata dummies. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 6: Impact of ACT and RDT Subsidy on Diagnosis Seeking and Medication Choice by Literacy and Predicted Malaria Probability

	All			Illiterate			Literate		
	Take ACT	Take Anti-biotic	Take Other	Take ACT	Take Anti-biotic	Take Other	Take ACT	Take Anti-biotic	Take Other
<i>Specification 1 – Main Effect</i>									
α	0.153*** (0.041)	-0.052 (0.045)	-0.071** (0.035)	0.272*** (0.056)	-0.008 (0.075)	-0.008 (0.075)	0.081 (0.057)	-0.062 (0.052)	-0.092 (0.056)
β	0.006 (0.027)	-0.002 (0.027)	0.022 (0.018)	-0.055 (0.046)	0.009 (0.027)	0.009 (0.027)	0.037 (0.035)	0.039 (0.019)	-0.015 (0.035)
p-val for F-Test $\alpha + \beta = 0$	0.000***	0.187	0.134	0.985	0.628	0.628	0.021**	0.894	0.035**
<i>Specification 2 – Impact by Predicted Probability</i>									
α_1	0.157*** (0.056)	0.054 (0.072)	-0.050 (0.051)	0.222*** (0.070)	-0.004 (0.112)	-0.004 (0.112)	0.122 (0.088)	-0.009 (0.075)	0.089 (0.096)
α_2	0.123 (0.079)	-0.089 (0.083)	-0.060 (0.068)	0.222 (0.143)	0.042 (0.168)	0.042 (0.168)	0.071 (0.096)	-0.165 (0.145)	-0.129 (0.094)
α_3	0.160* (0.083)	-0.175** (0.076)	-0.120* (0.064)	0.330*** (0.111)	-0.063 (0.122)	-0.063 (0.122)	0.021 (0.107)	-0.063 (0.076)	-0.282*** (0.090)
β_1	-0.029 (0.043)	-0.010 (0.046)	0.059* (0.033)	-0.032 (0.063)	-0.008 (0.070)	-0.008 (0.070)	-0.034 (0.060)	0.044 (0.048)	-0.016 (0.064)
β_2	0.013 (0.045)	-0.044 (0.046)	0.012 (0.032)	-0.112 (0.079)	-0.095 (0.086)	-0.095 (0.086)	0.074 (0.056)	0.016 (0.050)	-0.033 (0.056)
β_3	0.017 (0.046)	0.039 (0.046)	0.001 (0.028)	0.008 (0.088)	0.140 (0.087)	0.140 (0.087)	0.018 (0.055)	0.040 (0.044)	-0.011 (0.055)
p-val: $\alpha_1 + \beta_1 = 0$	0.007***	0.484	0.837	0.000***	0.907	0.907	0.258	0.595	0.383
p-val: $\alpha_2 + \beta_2 = 0$	0.062*	0.077*	0.465	0.404	0.730	0.730	0.097*	0.293	0.055*
p-val: $\alpha_3 + \beta_3 = 0$	0.020**	0.046**	0.053*	0.000***	0.478	0.478	0.690	0.753	0.000***
p-val: $\alpha_1 = \alpha_2 = \alpha_3$	0.929	0.082*	0.670	0.695	0.865	0.865	0.759	0.620	0.019**
p-val: $\alpha_1 + \beta_1 = \alpha_2 + \beta_2 = \alpha_3 + \beta_3$	0.861	0.090*	0.241	0.289	0.737	0.737	0.728	0.488	0.007***
DV Mean (Control Group)	0.259	0.494	0.185	0.108	0.446	0.446	0.365	0.138	0.531
N	2042	2042	2042	705	705	705	1332	705	1332

Notes: Robust standard errors in parentheses, clustered at household level. Regressions include first illness episode that occurred after baseline. A few households have more than one first illness episode if two family members were sick simultaneously. All regressions control for household head age and a full set of strata dummies. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively.

Table 7: Price Elasticity, Within ACT Subsidy Group

	(1)	(2)	(3)	(4)	(5)	(6)
	Administrative Data			Endline Data		
	HH Used ACT Voucher	HH Used ACT Voucher for Patient Age 13 or Below	HH Used ACT Voucher for Patient Age 14 or Above	Dep. Var:		
	HH Used ACT Voucher	HH Used ACT Voucher for Patient Age 13 or Below	HH Used ACT Voucher for Patient Age 14 or Above	Took ACT at First Illness Episode		
				All	Below	Above
<i>Specification 1: ACT Price Dummies (Omitted Category: ACT Subsidy = 92%)</i>						
ACT Subsidy = 88%	-0.027 (0.038)	0.032 (0.034)	-0.058** (0.027)	-0.042 (0.060)	0.001 (0.081)	-0.128 (0.087)
ACT Subsidy = 80%	-0.055 (0.037)	0.027 (0.034)	-0.082*** (0.026)	-0.017 (0.058)	0.021 (0.080)	-0.091 (0.083)
ACT 92% × RDT Subsidy	-0.005 (0.036)	0.023 (0.032)	-0.028 (0.027)	0.000 (0.052)	0.063 (0.069)	-0.107 (0.075)
ACT 88% × RDT Subsidy	0.005 (0.033)	0.024 (0.031)	-0.018 (0.021)	0.028 (0.046)	0.053 (0.061)	-0.008 (0.067)
ACT 80% × RDT Subsidy	-0.039 (0.032)	-0.035 (0.030)	-0.004 (0.019)	-0.007 (0.044)	0.011 (0.060)	-0.020 (0.061)
Mean DV (ACT 92%, no RDT)	0.439 2609	0.268 2609	0.171 2609	0.457 1880	0.462 1085	0.450 794
Total Effect (ACT 80% & RDT)	-0.094	-0.008	-0.086	-0.024	0.032	-0.112
P-val (ACT 80% & RDT)	0.004***	0.777	0.000***	0.625	0.633	0.111
<i>Specification 2: Linear ACT Price</i>						
ACT Price (US\$)	-0.069 (0.047)	0.028 (0.043)	-0.097*** (0.032)	-0.010 (0.073)	0.030 (0.101)	-0.085 (0.104)
RDT Subsidy	0.034 (0.057)	0.085 (0.052)	-0.051 (0.039)	-0.019 (0.085)	-0.071 (0.115)	0.093 (0.120)
ACT Price (US\$) × RDT Subsidy	-0.054 (0.060)	-0.091 (0.055)	0.037 (0.040)	0.022 (0.081)	0.103 (0.108)	-0.128 (0.115)
Mean DV (No RDT)	0.414 2609	0.291 2609	0.123 2609	0.426 1880	0.490 1085	0.344 794

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

Table 8: Targeting Effects of ACT Price and RDTs

Subsample	Redemptions at the Drug Shop (Administrative Records)				Endline First Illness Episodes			
	Sought Treatment at Drug Shop		Took ACT at Drug Shop		Sought Treatment		Took ACT	
	Treated Positive	Predicted Positivity	Tested Positive	Predicted Positivity	All Treatment	Sought Treatment	ACT	ACT
<i>Dependent Variable</i>								
<i>Specification 1: ACT Price Dummies (Omitted Category: ACT Subsidy = 92%)</i>								
ACT Subsidy = 88%	-0.028 (0.038)	0.194*** (0.080)	0.073* (0.041)	0.187** (0.080)	-0.027 (0.058)	0.061 (0.040)	0.057 (0.044)	0.057 (0.044)
ACT Subsidy = 80%	-0.059 (0.037)	0.190** (0.083)	0.108*** (0.040)	0.182** (0.084)	-0.010 (0.056)	0.019 (0.040)	0.030 (0.043)	0.030 (0.043)
ACT 92% × RDT Subsidy	0.028 (0.036)	0.127* (0.070)	0.037 (0.036)	0.163** (0.070)	0.022 (0.050)	0.051 (0.034)	0.053 (0.036)	0.053 (0.036)
ACT 88% × RDT Subsidy	0.054 (0.033)	-0.058 (0.063)	-0.020 (0.032)	0.018 (0.062)	0.044 (0.044)	-0.023 (0.031)	-0.001 (0.035)	-0.001 (0.035)
ACT 80% × RDT Subsidy	0.017 (0.032)	-0.047 (0.068)	-0.071** (0.032)	0.061 (0.067)	-0.009 (0.042)	0.027 (0.031)	0.021 (0.033)	0.021 (0.033)
<i>Specification 2: Linear ACT Price</i>								
ACT Price (US\$)	-0.074 (0.047)	0.224** (0.107)	0.133*** (0.051)	0.214** (0.107)	-0.005 (0.070)	0.007 (0.051)	0.025 (0.054)	0.025 (0.054)
RDT	0.058 (0.057)	0.183 (0.113)	0.104* (0.057)	0.181 (0.113)	0.065 (0.077)	0.026 (0.054)	0.052 (0.057)	0.052 (0.057)
ACT Price (US\$) × RDT	-0.027 (0.061)	-0.205* (0.124)	-0.141** (0.061)	-0.116 (0.123)	-0.053 (0.081)	-0.009 (0.058)	-0.030 (0.061)	-0.030 (0.061)
N	2609	755	752	687	2090	975	816	816

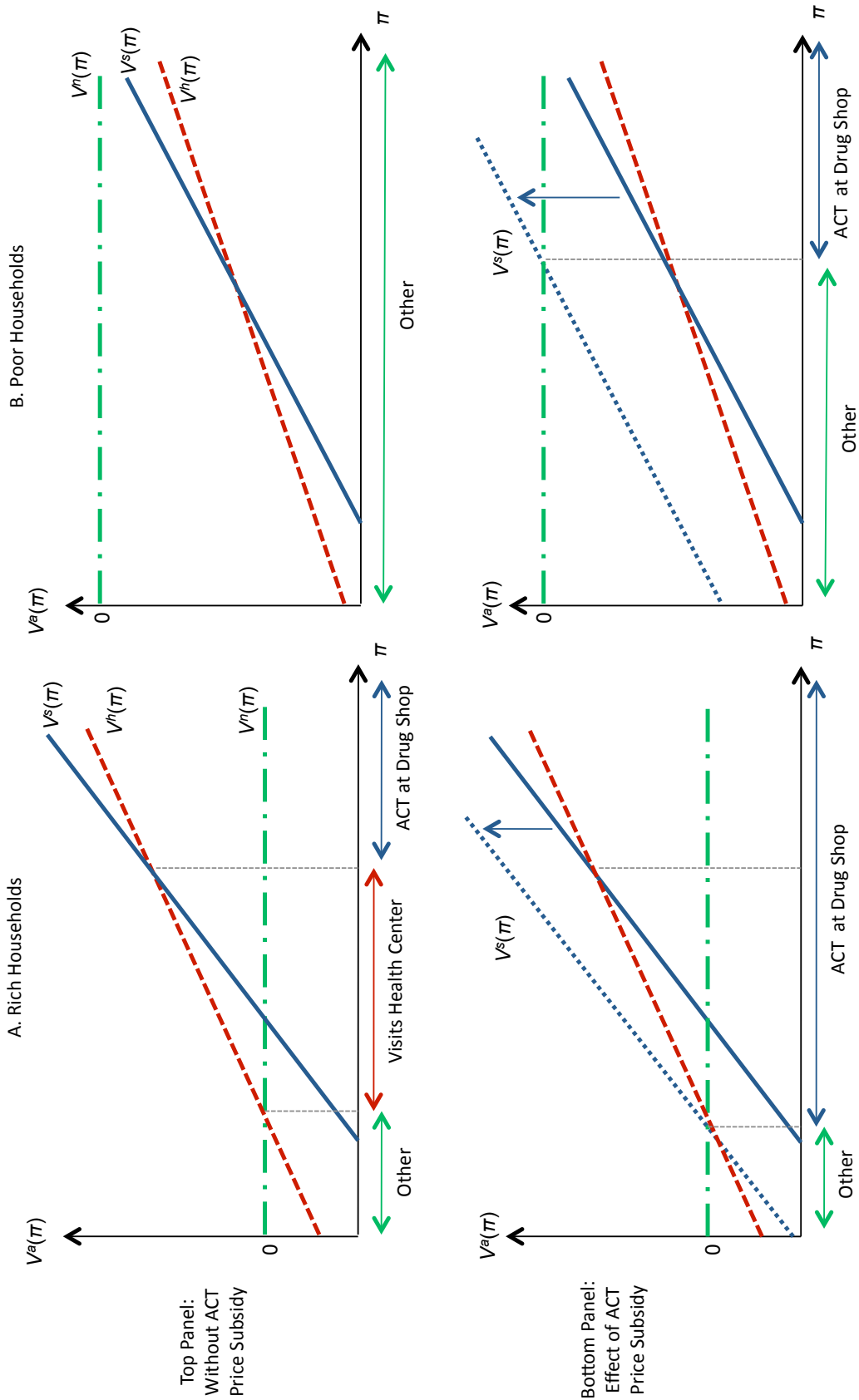
Notes: Robust standard errors in parentheses, clustered at the household level when applicable (columns 6-9). Regressions on "sought treatment" control for a full set of strata dummy variables and household head age. ***, **, and * indicate significance at the 99, 95, and 90 percent levels respectively. Drug shop results – "sought treatment" and "took ACT" only at drug shop. Endline results – "sought treatment" and "took ACT" include all health care channels.

Table 9: Cost Effectiveness Estimates

	UT: Share Malaria+	OT: Share Malaria- Treated With ACT	T: Fraction of ACT Takers Who Are Malaria+	Cost/Malara Episode	Cost/ACT to Malaria Positive Episode	Share of Total Subsidy Budget Spent on Malaria+
<i>A. Actual RDT Adherence</i>						
ACT 92%	0.550	0.414	0.676	0.669	1.49	0.605
ACT 92% - RDT	0.517	0.370	0.705	0.879	1.82	0.654
ACT 88%	0.548	0.392	0.687	0.636	1.41	0.620
ACT 88% - RDT	0.523	0.366	0.708	0.826	1.73	0.659
ACT 80%	0.543	0.349	0.711	0.573	1.25	0.653
ACT 80% - RDT	0.536	0.357	0.713	0.722	1.55	0.669
<i>B. Perfect RDT Adherence</i>						
ACT 92%	0.550	0.380	0.683	0.665	1.48	0.609
ACT 92% - RDT	0.517	0.122	0.830	0.768	1.59	0.748
ACT 88%	0.548	0.347	0.697	0.626	1.38	0.630
ACT 88% - RDT	0.523	0.140	0.820	0.731	1.53	0.744
ACT 80%	0.543	0.282	0.727	0.556	1.21	0.674
ACT 80% - RDT	0.536	0.174	0.799	0.657	1.42	0.735

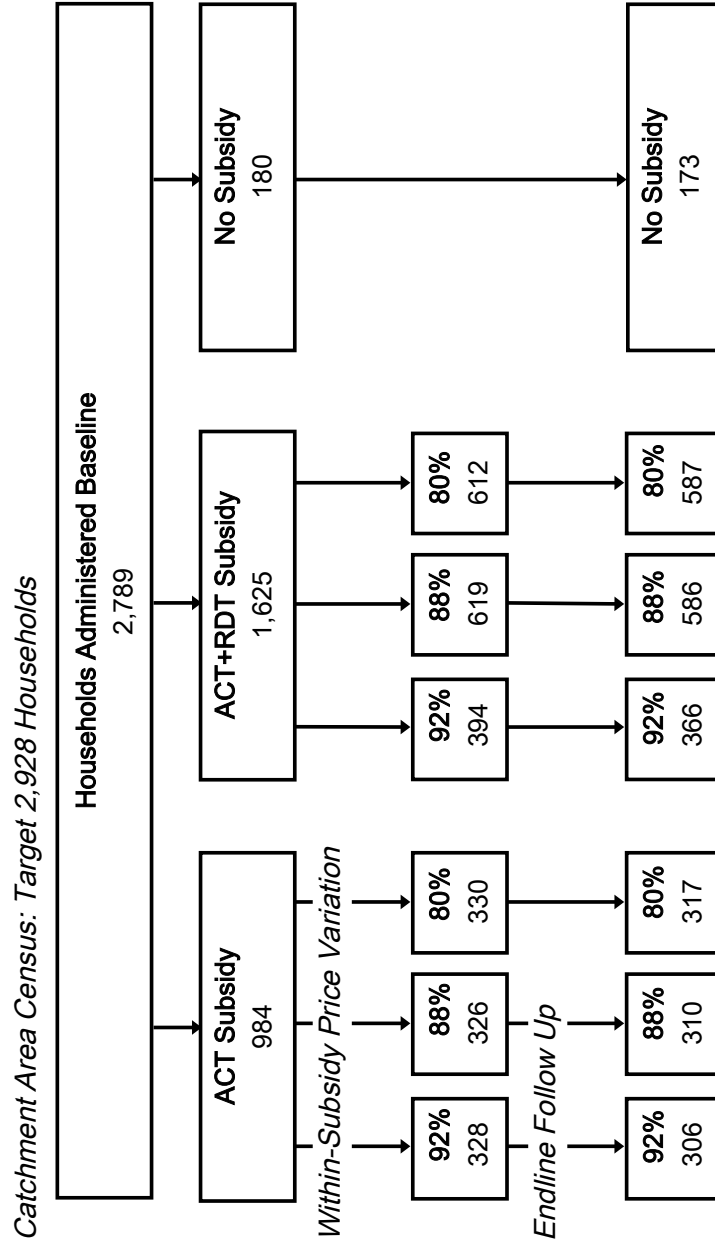
Notes: Assumes unsubsidized costs of \$1.46, \$1.20, \$0.84, and \$0.43 for ACT doses for adults, teens, children, and infants respectively. Assumes \$0.53 subsidy cost for RDTs. "Care seekers" are defined to be patients purchasing an ACT in the ACT-only regimes and patients purchasing an ACT or RDT in the ACT-RDT regimes. The perfect RDT adherence scenario assumes perfect compliance with RDT test results (for ACT-RDT regimes only) and no change in RDT take-up.

Figure 1: Theoretical Treatment Seeking Scenarios



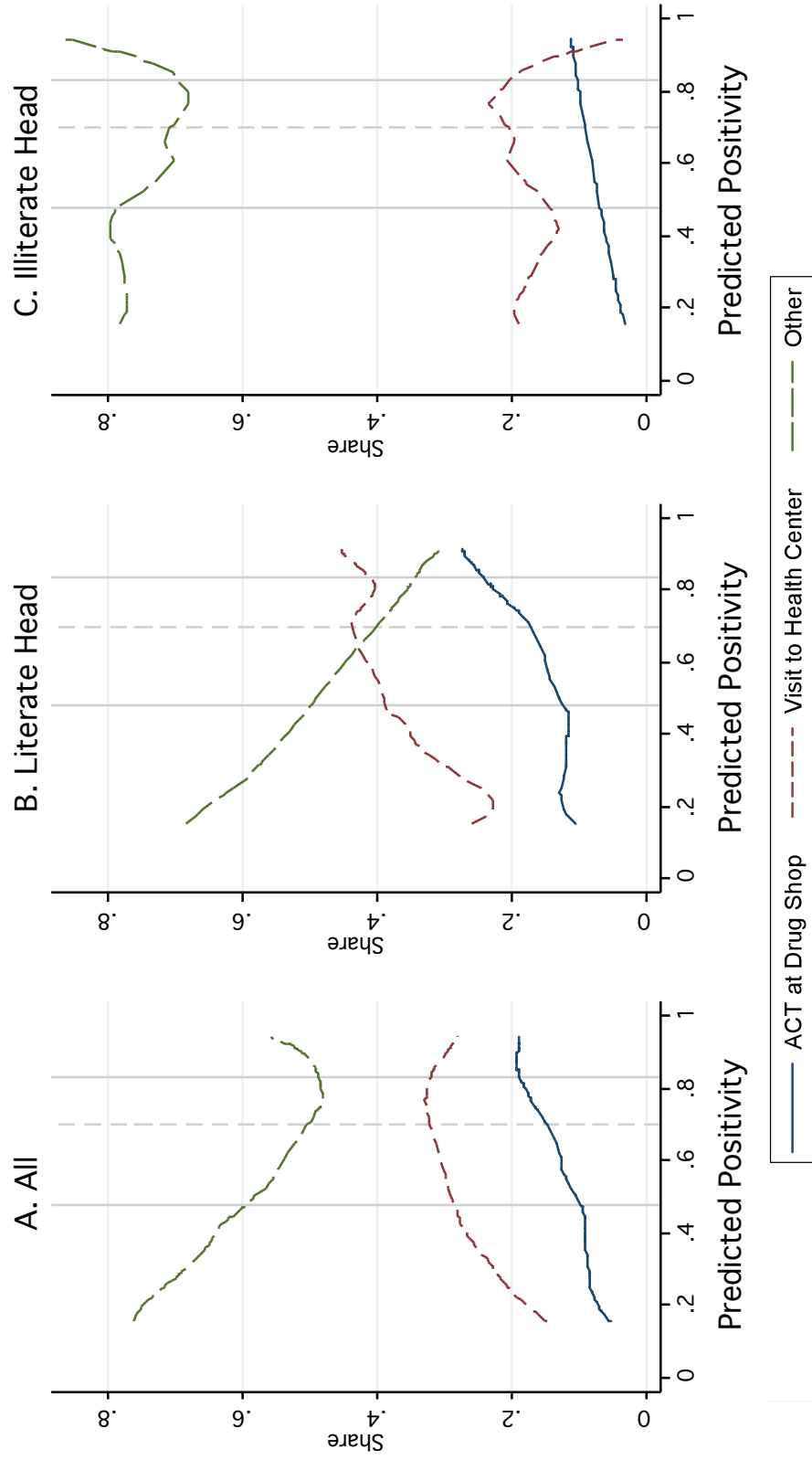
Notes: π is the (perceived and actual) probability that the illness episode is malaria. V^s is the value of purchasing an ACT at the drug shop; V^h is the value of visiting a health center and receiving free ACT if positive; V^n is the value of doing neither of the two options above. The value functions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

Figure 2: Experimental Design and Attrition: Number of Households per Study Arm



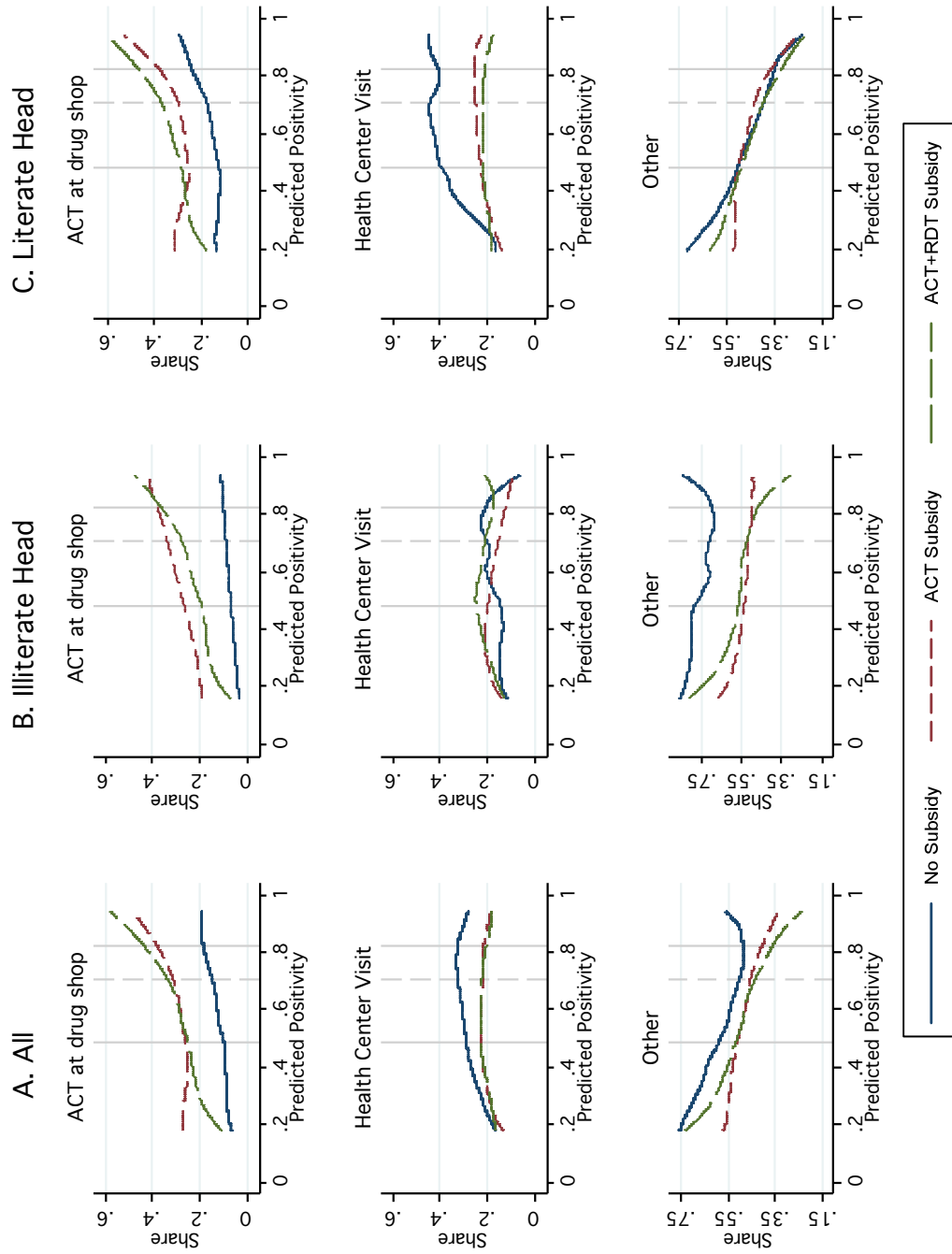
Notes: 49 percent of ACT subsidy only households and 80 percent of ACT+RDT Subsidy households were selected for surprise RDT testing at the drug shop.

Figure 3: Baseline Malaria Treatment Seeking Behavior by Predicted Positivity and SES



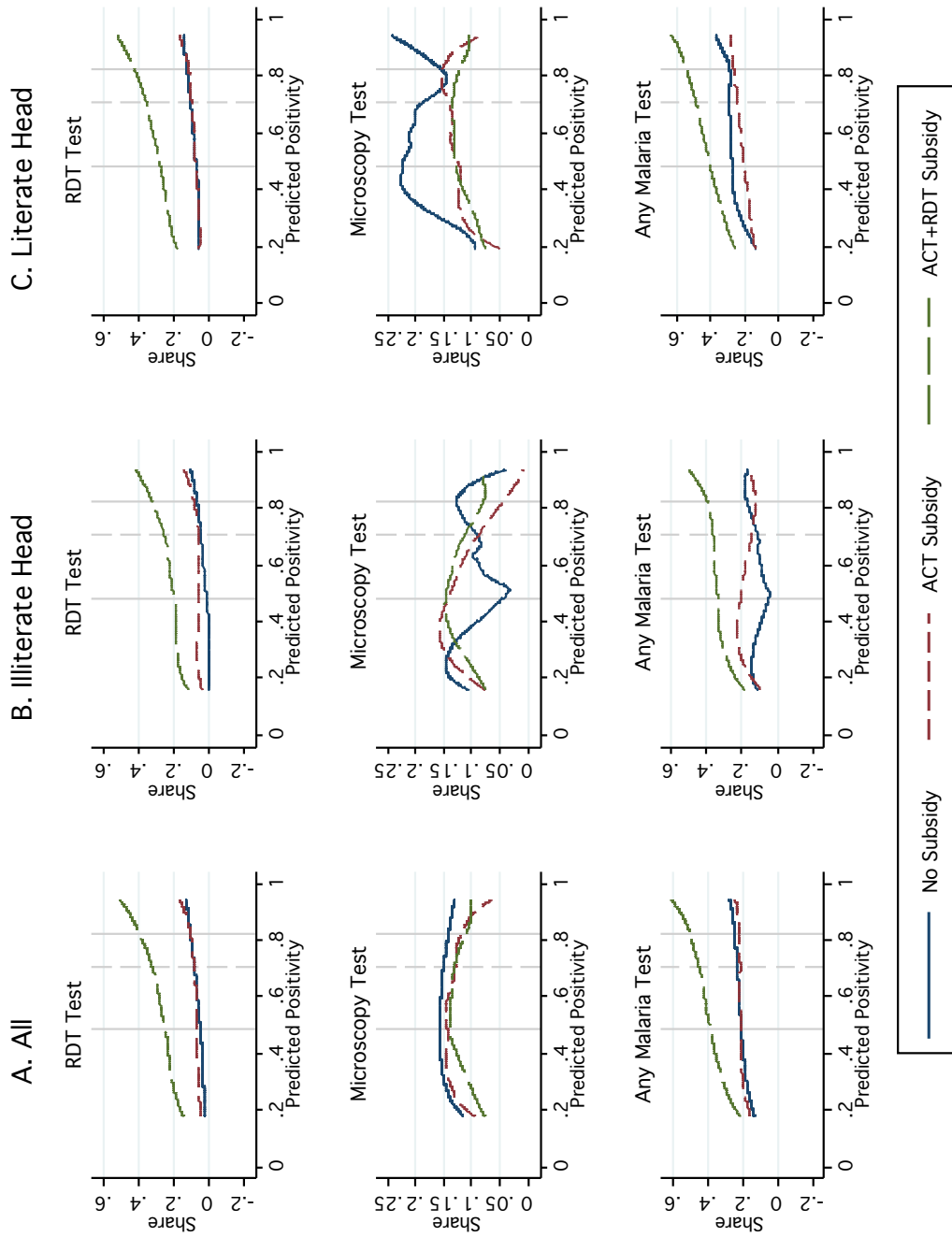
Notes: Data from "No Subsidy" group. Local linear regression lines trimmed at 2.5 percent. Tertiles demarcated by gray vertical lines. Median demarcated by dashed gray vertical line.

Figure 4: Impacts of Subsidy Regimes on Treatment Seeking Behavior by Predicted Positivity and SES



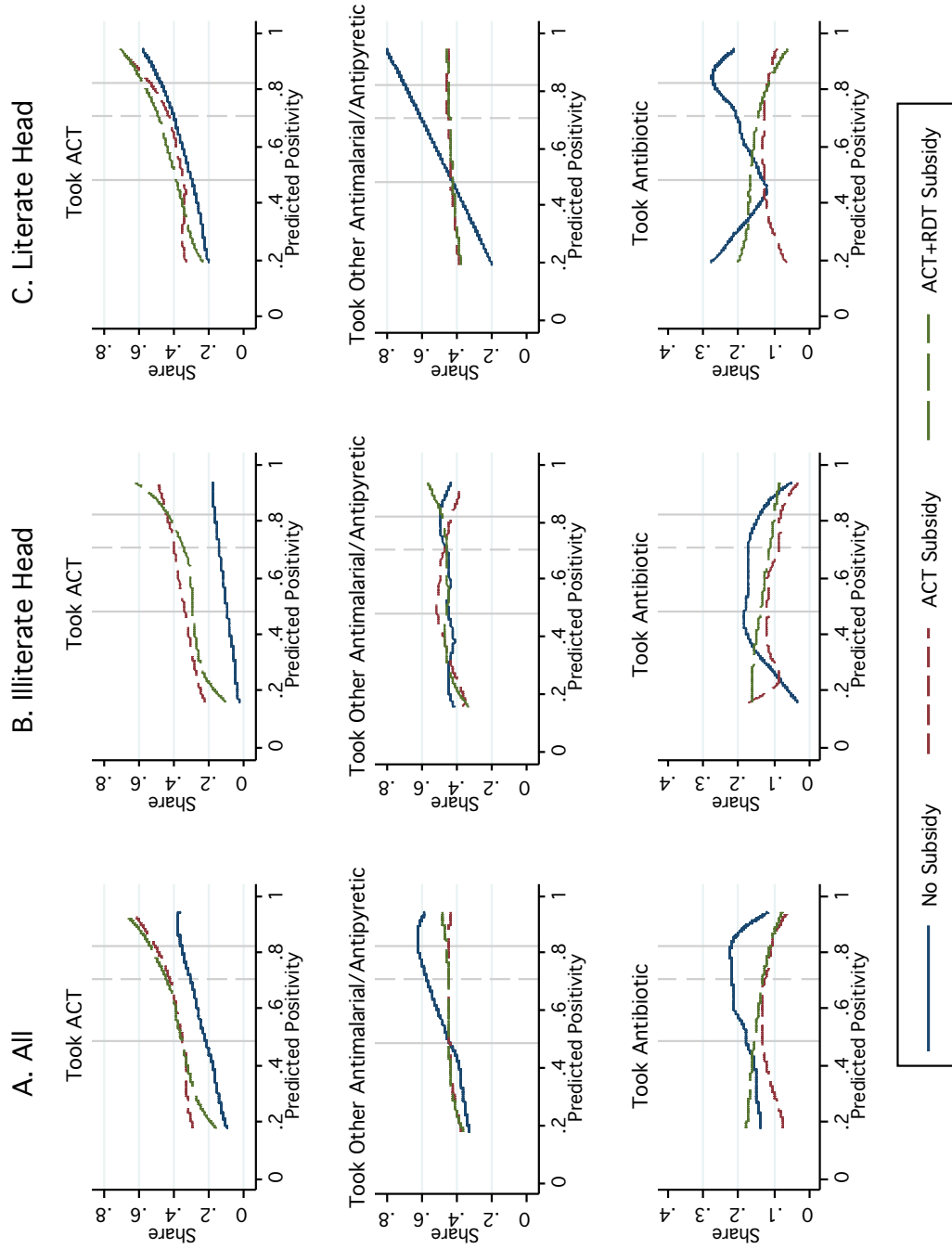
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Excludes households without RDT vouchers but randomly selected for surprise RDT testing at drug shop.

Figure 5: Malaria Testing by Predicted Positivity, Subsidy Treatment and Head Literacy



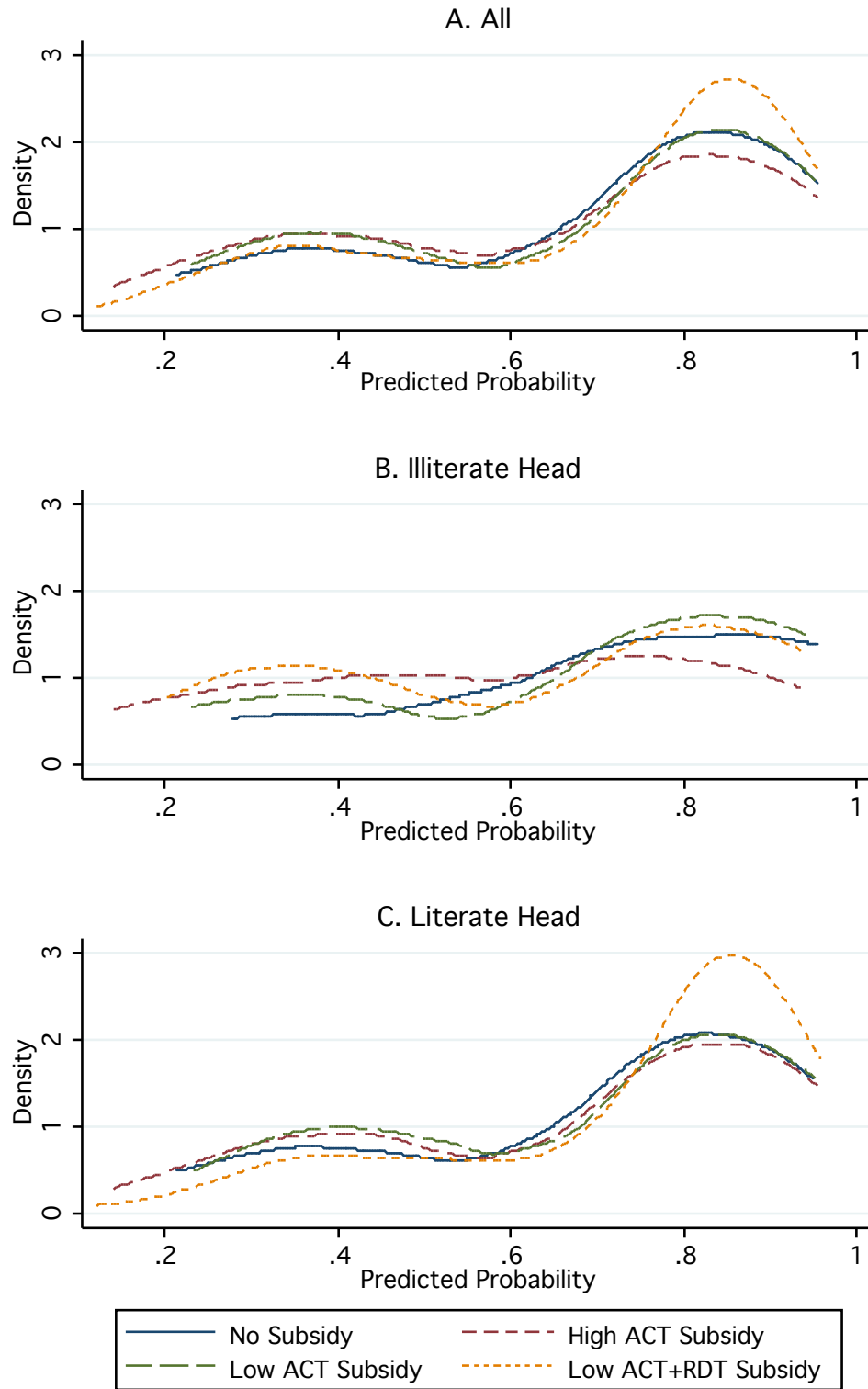
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Excludes households without RDT vouchers but randomly selected for surprise RDT testing at drug shop.

Figure 6: Drug Choice by Predicted Positivity, Subsidy Treatment and Head Literacy



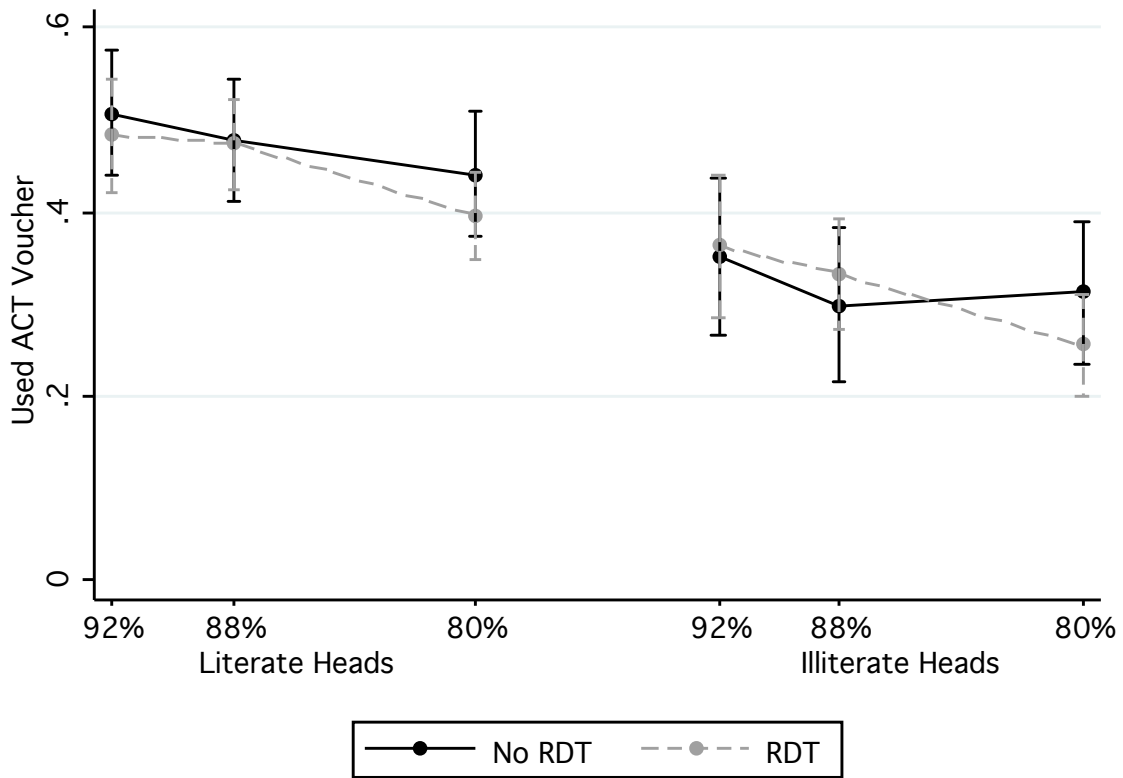
Notes: Local linear regression lines trimmed at 2.5 percent. Gray vertical lines demarcate tertiles. Excludes households without RDT vouchers but randomly selected for surprise RDT testing at drug shop.

Figure 7: 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.

Figure 8: Drug Shop ACT Demand by SES



Notes: Figure plots predicted values and 95 percent confidence intervals from regression estimates using heteroskedasticity robust standard errors. Regressions include controls for age of the household head and strata. These variables are evaluated at sample means when calculating predicted values.

Table A1: 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 (0.020)	0.024 (0.157)	0.037 (0.023)	1.73 (3.86)	-1.71 (1.65)
ACT 88%	0.002 (0.021)	-0.063 (0.155)	0.039* (0.023)	4.72 (3.75)	-2.92* (1.61)
ACT 80%	-0.020 (0.021)	-0.168 (0.155)	0.031 (0.023)	3.19 (3.78)	-1.69 (1.62)
Any RDT	0.006 (0.010)	-0.025 (0.078)	0.004 (0.010)	-1.27 (1.87)	0.906 (0.777)
Ex-Post Tested	0.001 (0.010)	0.089 (0.079)	-0.017 (0.011)	5.09*** (1.95)	0.988 (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.

Figure A1: ACT Voucher and Translation

ID:


Bei nafuu kwa wagonjwa wanaouguua malaria!


Peleka hii kadi:

Kwa Duka la Dawa la Funyula Chemist
Lililo karibu na Pop Inn Hotel

Ili kupata dawa ya malaria ya Coartem (AL):

Ksh 100/- walio na umri wa miaka 14 au zaidi
Ksh 75/- watoto kati ya miaka 9 hadi 13
Ksh 50/- watoto kati ya miaka 4 hadi 8
Ksh 25/- watoto wa umri wa miezi 3 hadi miaka 3





FO ID:

Date:

A special value for those sick with malaria!

Bring this card to:

Funyula Chemist

Directions

To obtain the anti-malarial Coartem at a special price:

Ksh 100/- for individuals 14 and older

Ksh 75/- for children aged 9-13

Ksh 50/- for children aged 4-8

Ksh 25/- for children aged 3 months-3 years

Kadi inakubalika kuanzia saa tatu – hadi saa kumi na moja (Jumatatu hadi Jumamosi)

Coartem (artemether–lumefantrine, or AL) ni dawa mpya ya malaria iliyo na nguvu kuliko dawa zingine za malaria.

Hii kadi inakuwezesha kununua dawa ya malaria ya coartem iwapo mtu atangojeka kwa nyumba yako. Lazima mtu huyo aje na hii kadi kwenye duka la dawa ili aweze kununua dawa hii. Kumbuka: Bei ni tofauti kulingana na umri kwa sababu watoto humeza kiwango kidogo kuliko watu wazima.

Muhimu: Watoto chini ya miezi 3 na wamama wajawazito kwa miezi 3 za kwanza hawatajikani kumeza hii dawa ya Coartem

This voucher can only be redeemed from 9AM-5PM Monday-Saturday

Coartem (artemether–lumefantrine, or AL) is a new anti-malaria drug that is more effective than other drugs currently available to you.

This card may only be used to purchase Coartem for someone in your household. A household member must come with this card to the chemist to make the purchase. Note: dose prices vary by age because children need less medicine than adults.

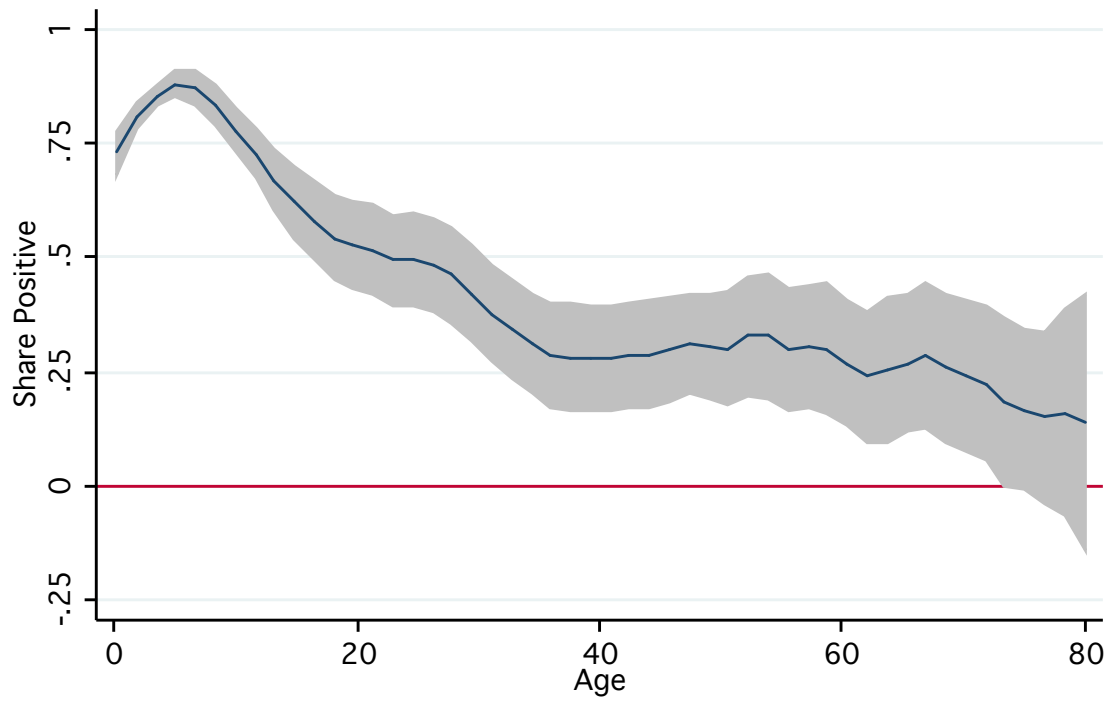
It is important that infants under the age of 3 months and women in the first trimester of pregnancy do not take Coartem.

Notes: Figure shows voucher front, front translation, voucher back, and back translation respectively.

Figure A2: ACT Price and Dosing Guide

		<i>Recommended Dose and Corresponding Dose Cost for:</i>			
		Adult (14+)	Ages 9-13	Ages 4-8	Ages 3m-3y
<i>Dose</i> <i>Price Per Pill</i>		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 (92% 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 (80% subsidy)	Ksh 40	Ksh 30	Ksh 20	Ksh 10

Figure A3: Age and Malaria Positivity (Drug Shop Treatment Seekers)



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