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ABSTRACT

Can Good Products Drive Out Bad? Evidence from Local Markets for (Fake?) Antimalarial Medicine in Uganda*

Counterfeit and sub-standard antimalarial drugs present a growing threat to public health. This paper investigates the mechanisms that determine the prevalence of fake antimalarial drugs in local markets, their effects, and potential interventions to combat the problem. We collect drug samples from a large set of local markets in Uganda using covert shoppers and employ Raman spectroscopy to test for drug quality. We find that 37 percent of the local outlets sell fake antimalarial drugs. Motivated by a simple model, we conduct a market-level experiment to test whether authentic drugs can drive out fake drugs from the local market. We find evidence of such externalities: the intervention reduced prevalence of substandard and counterfeit drugs in incumbent outlets by half. We also provide suggestive evidence that misconceptions about malaria lead consumers to overestimate antimalarial drug quality, and that opportunistic drug shops exploit these misconceptions by selling substandard and counterfeit drugs. Together, our results indicate that high quality products can drive out low quality ones, but the opposite is true when consumers are less able to infer product quality.

JEL Classification: D83, I15 and O12
Keywords: act, asymmetric information, counterfeit medicine, field experiment and malaria

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1 Introduction

Worldwide, 3.3 billion people are at risk of malaria, and the disease kills 660,000 to 1.2 million people every year, with up to 90 percent of the deaths occurring in sub-Saharan Africa (WHO, 2011a; Murray et al., 2012). A large share of these deaths could be prevented if high quality and effective drugs were available to patients.

Antimalarial drugs in endemic regions are typically purchased directly by the patient or the caregiver in local markets (e.g., from drug shops, pharmacies, itinerant drug sellers). There is growing evidence, however, that local markets are often plagued by bad quality medicines, with a third of the antimalarial drugs used estimated to be counterfeit (Nayyar et al., 2012).[1] While evidence is mounting about the extent of the problem, little is known about the mechanisms that determine the prevalence of fake medicines, their effects in local markets, and potential interventions to combat this problem.[2]

In this paper we combine data on direct measures of artemisinin-based combination therapy (ACT) quality with market structure data and household survey data from 99 villages in four Ugandan districts.[3] We first use the data to establish some basic facts about local markets. Specifically we show that 37% of the private drug shops, a majority of them local monopolies, sell fake ACT drugs. Second, we show that prices do not signal quality across outlets within the same local market, a result consistent with Akerlof (1970), but which stands in contrast with existing models of experience goods (Wolinsky, 1982; Milgrom and Roberts, 1986), or models with adaptive learning and reputation (Shapiro, 1982). Third, we find evidence suggesting that households are able to infer quality, although not perfectly: households that suspect a higher fraction of fake drugs also tend to live in villages where fake drugs are more common, but many households living in villages with fake drugs believe that no fake drugs are sold. Finally, we show that misconceptions about how malaria is transmitted are common.

To understand the determinants of drug quality and to guide the empirical work, we first present

[1] In a meta-analysis of published and unpublished work reporting chemical analyses of antimalarial drugs in southeast Asia and sub-Saharan Africa, Nayyar et al. (2012) estimate that 32% of the tested samples were falsified, meaning the sample contained too little or no active pharmaceutical ingredients, or contained an unstated drug or substance. They conclude that poor-quality antimalarial drugs, particularly artemisinin, are likely to jeopardize the unprecedented progress and investments in control and elimination of malaria made in the past decade. Poor quality ACTs can have both direct short and long run adverse effects on health outcomes by failing to reduce the parasite load or delaying treatment with high quality medicines. To the extent that poor quality medicines contain sub-therapeutic amounts of the active pharmaceutical ingredients, the sale of substandard ACTs can also lead to the development of ACT resistance.

[2] Poor quality drugs are counterfeit or falsified drugs where there has been a deliberate and fraudulent mislabeling of the medicine with respect to identity and/or source, and with usually no or wrong active pharmaceutical ingredients, or of sub-standard quality (where poor practices on behalf of the authorized manufacturer result in inadequate content). We use the term fake drugs for drugs that fail chemical analyses using Raman spectroscopy (see section 3).

[3] ACT is the first-line WHO recommended treatment for malaria.

a simple model of the market under local monopoly. The model takes its starting point in the evidence discussed above. In particular, consumers (patients) face uncertainty as to whether they have malaria or some other febrile disease (e.g., a viral or bacterial disease). Drug quality is unobservable before purchase, and prices do not signal quality, but consumers may still partially infer quality by observing health outcomes after taking the drugs. Moreover, biomedical misconceptions about malaria are common leading some consumers to incorrectly diagnose self-limiting febrile illnesses (due to bacterial and viral infections) as malaria.[4] The model delivers a set of testable predictions as to how drug quality is determined under local monopoly. A key result is that the reputational incentive to sell high quality drugs is lower when consumers are less able to correctly infer quality. Therefore, when misconceptions about malaria are more common, bad drugs will tend to drive out good drugs from the market.

We then present a set of correlations consistent with the predictions of the model. First, beliefs about drug quality matter for demand, even conditional on price and actual quality. Second, misconceptions about malaria hampers learning and leads 'naive' consumers to overestimate antimalarial drug quality. In markets where these misconceptions are more common, we find that drug shops are more likely to sell fake drugs. This is consistent with the hypothesis that selling low quality drugs is optimal for drug shops when many consumers are naive, as the reputation forces are then weaker.

We then address the main question of the paper: Can high quality products, in markets plagued by low quality, drive out low quality products? Since Akerlof's (1970) seminal paper, it is well known that markets are inefficient when quality is unobservable, as 'bad quality tends to drive out good quality'. However, less is known about the opposite relationship; i.e., can a seller committed to high quality force other sellers to increase quality when quality is not directly observable, and if so under what conditions? In a context where state capacity to regulate and monitor markets is weak, this question is of particular importance.

To investigate this question, we conduct a randomized experiment across the 99 local markets in our sample. In the spirit of Akerlof's (1970) discussion of counteracting the market for lemons problem, we collaborated with a local NGO and randomly assigned community health promoters that, using the brand name of the NGO, sold authentic ACT drugs below market prices in the villages.

The intervention increased the share of authentic ACTs sold by the incumbent drug shops by 11 percentage points, corresponding to a decrease in fake drugs of approximately 50 percent. The intervention also reduced the price charged by incumbent drug shops by almost 20 percent. Lower prices and higher quality increased the use of ACT medicines by children by almost 40 percent.

[4]Self-limiting diseases in this case are bacterial or viral infectons sharing symptoms with malaria and tending to end without treatment.

Finally, we find that the treatment effects on drug quality are decreasing in the share of naive consumers in the market.

We interpret the treatment effects through the lens of our model. When a seller committed to high quality (the NGO) enters the market, consumers' ability to infer quality (differences) improves. This forces the incumbent drug shop to sell fewer fake drugs in order to not lose his reputation and thus market share. As consumers are able to partly infer drug quality by observing health outcomes, consumers then also expect fewer fake ACT:s in drug shops. As the new entrant charges a lower price, the incumbent is also forced to lower prices to remain competitive. Lower prices and higher quality, in turn, increase demand. Finally, as consumers with misconceptions about malaria are less able to correctly infer quality, the reputational incentive is weaker for the incumbent drug shop in markets where naive consumers are relatively more prevalent. Together, our results indicate that 'good products can drive out bad', but the opposite mechanism tends to dominate when consumers are less able to correctly infer quality.

Antimalarial drugs form part of a wider set of products where quality *is not directly observable* at the time of the purchase and only *partially observable when used*.[5] Thus, while we focus on a particular – albeit an important – market, our findings are of more general interest beyond pharmaceutical products. Evidence and news reports suggest that product quality in markets in developing countries is notoriously low due to the counterfeiting of many experience goods such as fertilizers and seeds, gasoline, auto parts, electronics, baby food, and hygiene products (Tanzania Daily News, 2012; East African Business Week, 2012; India Daily News, 2012; OECD, 2008). Studying markets for these products is important not only because trade will be suboptimally low, but especially since poor product quality for inputs can directly affect productivity and also people's willingness to experiment and adopt new technologies. Furthermore, even if these differences are small for each input, they could result in large differences in aggregate output (Kremer, 1993). Moreover, while counterfeit medicines have traditionally been more of a concern in developing regions, where regulatory and enforcement systems for medicines are weak, counterfeiting has become more and more prevalent in developed countries as drug supply chains increasingly cross continents through online markets (Lancet, 2012). Across all tangible products, international trade in counterfeit goods is estimated to 250 billion USD, and when domestically produced and consumed goods are included, the magnitude of counterfeiting worldwide is estimated to be over 600 billion USD (OECD, 2008; BASCAP, 2011).

There is a large theoretical and empirical literature on markets with unobserved product quality, and in particular, markets for experience goods. Our work is related, but differs in important ways. First, in the model, antimalarial drug quality can only be assessed indirectly by observing and

[5]These goods thus process attributes similar to both "experience goods" (learn about quality after purchase) and "credence goods" (never learn about quality).

comparing health outcomes.[6] Second, empirically, we measure quality directly and relate this to prices and beliefs about quality. Third, and most importantly, we provide experimental evidence from an intervention aimed at changing the market equilibrium.

The paper is structured in the following way. Section 2 describes important features common to antimalarial markets. Section 3 describes the data and the experimental design. It also establish some basic facts about local markets. Section 4 presents the model and discusses its implictions. The empirical design is described in section 5. Section 6 presents both simple correlations and the experimental results. Section 7 concludes.

2 The Market for Antimalarial Drugs: Demand and Supply

To understand the potential mechanisms determining how local drug stores set antimalarial quality, this section describes the basic features of the antimalarial drug market in Uganda. These features are not specific to Uganda, however, as evidence from other Sub-Saharan African countries illustrate. We first describe features one can view as determining consumer demand, broadly defined, followed by factors influencing the supply side.

2.1 Demand

We first characterize the demand side of the market, starting with the disease, its symptoms, and treatment. We then highlight three features of the demand side that are likely to affect drug quality. First, the general symptoms of malaria overlap with several other diseases, making it difficult, lacking diagnostic tests, for a consumer to know with certainty whether she has malaria or some other febrile disease. Second, when experiencing symptoms of malaria, consumers often self-treat without testing for the underlying cause. Third, evidence from medical anthropology shows that misconceptions about the causes of malaria are common.

2.1.1 The Disease: *P. Falciparum* Malaria and Treatment

Plasmodium falciparum, the most severe form of malaria and the most common type in Sub-Saharan Africa, is responsible for the vast majority of deaths associated with malaria. The disease is a mosquito-borne infectious disease and results from the multiplication of parasites within the host's red blood cells causing symptoms that typically include fever and headache. In severe cases,

[6] In this respect, we are most closely related to Kremer and Miguel (2007) who also investigate consumer learning about the quality of medicines. The paper also relates to the literature on (unobserved) provider quality in the health sector in developing countries (see for instance Das et al. (2008) and the reference given therein).

it progresses to coma or death. In Africa alone there were 174 million cases of malaria in 2010 and an estimated 596 000 to over 1 million deaths, most of them children under five (WHO, 2011; Murray et al., 2012). Uganda has one of the world's highest malaria incidences, with a rate of 478 cases per 1000 population per year (World Malaria Report, 2005, WHO).

Adequately and promptly treated, malaria is a curable disease but severe malaria can develop from seemingly uncomplicated and untreated cases within hours. Within 24-hour treatment of malaria is important in order to reduce the likelihood of morbidity, severe damages, and prevent death from malaria (Getahun et al., 2010). Artemisinin-based combination therapy (ACT) is currently recommended by WHO as the first-line treatment of *Plasmodium falciparum* malaria. Multiple brands of ACTs exist and the retail price for a dose in Sub-Saharan Africa is around 4-8 USD. Compared to older, synthetic forms of malaria medicine, artemisinin is significantly more expensive to produce.

Poor quality ACTs can have direct adverse effect on health outcomes by failing to reduce the parasite load or delaying treatment with high quality medicines. It can also have long run adverse effects. A 2006 systematic review of 18 studies concluded that untreated or inadequately treated *plasmodium falciparum* malaria during childhood affects short- and long-term neurocognitive performance (Kihara et al, 2006) and through higher risk of anemia, adversely impact cognitive development (Shi et al, 1996).[7] Because poor quality medicines can contain sub-therapeutic amounts of the active pharmaceutical ingredients, the sale of substandard ACTs can also lead to development of ACT resistance. According to the World Health organization, a key priority to prevent ACT resistance is the removal of substandard and counterfeit antimalarial medicines from the market (WHO, 2011b).

2.1.2 Unobservability of Malaria: Differential Diagnoses

Amexo et al. (2004) report that over 70% of malaria cases in Africa are diagnosed at home. Thus, symptomatic diagnosis of malaria is the norm.[8] However, as many infectious diseases mimic malaria both in initial symptoms and in signs of severe illness, diagnosis by symptoms alone can be highly misleading. Reviewing over 600 documents on malaria diagnosis in developing countries, Amexo et al. (2004) estimate a mean overestimation rate by symptomatic diagnosis, as compared to blood slide microscopy, of 61%. Cohen et al. (2011) report a similar finding: only 38 percent of adults who seek treatment for malaria at drug shops in Kenya actually have malaria.

[7] Recent estimates, based on quasi-experimental methods, also suggest a positive effect of malaria reduction on income and human capital attainment (Barecca, 2009, Barofsky, 2011; Bleakley et al, 2010; Cutler et al, 2010). Acemoglu and Johnson (2007), in contrast, argue that the wave of international health innovations that began in the 1940s did not lead to a disproportionate increase in log per capita GDP in the areas with high pre-intervention disease burden.

[8] The WHO recommends that all cases of suspected malaria be confirmed using parasite-based diagnostic testing.

The difficulty for an individual to receive a correct diagnosis is compounded by the fact that diagnosis of malaria in public primary health facilities is often based solely on clinical features such as fever. Even when blood slide microscopy, considered to be the gold standard for malaria diagnosis in laboratory situations, is available, it is often not used and has low accuracy in the field (Amexo et al., 2004).[9] A test of accuracy of routine malaria microscopy performed in health clinics in two districts in Kenya, for example, showed that approximately four of five reported positive malaria blood slides were in fact negative (Zurovac et al., 2006). Compliance with test results, both by individuals and health practitioners, is also weak.[10] Moreover, rapid diagnostic tests (RDTs), which have been shown to be highly accurate and can be performed by non-clinical staff, are either not available or priced too high for consumers to demand and use, particularly in rural areas (Cohen et al., 2011)

Misdiagnosis of malaria has a direct effect on households' health and socio-economic welfare as individuals wrongly diagnosed with malaria will be unnecessarily exposed to harmful side-effects of the drugs, and the true cause may be treated with delay or not treated at all, leading to prolonged and worsening illness. Misdiagnosis may also hamper households' ability to learn about antimalarial drug quality, and thus may have implications for drug quality on local markets.

2.1.3 Self-Treatment

In most of Africa, and in particular in rural areas and among poorer households, diagnosis and treatment of malaria is largely done at home using either traditional remedies or drugs bought from local shops (Amexo et al., 2004). WHO (2011) estimates that 72 percent of those that seek treatment for febrile children in Africa seek treatment from various private providers, with informal and unregulated private outlets being the most common provider.

Studies on health seeking behavior document similar patterns. For example, Nuwaha (2002), using household survey data from rural areas in the Mbarara district in Uganda, reports that 70 percent of the patients that sought treatment for malaria received treatment from non-public health sources. Citing the proximity as the main reason, as well as recurrent stock-outs, Rutebemberwa et al. (2009) find that two thirds of febrile children in a predominantly rural area in the Eastern region of Uganda were treated at home with drugs from informal drug shops and private clinics.[11]

[9] Maintaining a high quality microscopy service is a major challenge for primary health clinics as blood slide microscopy depends on well-maintained equipment, supply of good-quality reagents, and experienced and trained lab technicians.

[10] Juma and Zurovac (2011) find that 50 percent of patients who tested negative on the microscopic test for malaria were prescribed antimalarials regardless.

[11] For example, Bold et al (2011) find that 22% of the clinics did not have any ACTs in stock in a representative sample of 170 primary health clinics in Tanzania. Bjorkman and Svensson, 2009, show that public dispensaries in rural areas in Uganda had stock-outs (no availability of drugs) in 6 out of 12 months in 2005.

2.1.4 Misconceptions About Malaria

Evidence from medical anthropology suggests that misconceptions about how malaria is transmitted and treated are common. While it is well known that malaria is transmitted through mosquito bites, there are also a number of other common beliefs about what causes malaria. In a study of women's perceptions about malaria in Uganda, for example, malaria was mentioned as a major health problem by most respondents and it was also well-known that malaria is caused by mosquitoes (Nuwaha, 2002). However, most of those who reported that malaria is caused or transmitted by mosquitoes had an explanatory model that differed from the biomedical one. Specifically, only a minority believed that malaria is transmitted through the bite of mosquitoes. A majority of the respondents instead argued that malaria is transmitted by drinking mosquito eggs or larvae in dirty water. Interacting with somebody with malaria was also found to be a common cause of malaria and a significant fraction of the respondents also believed that eating fruits, such as mangos, infected with mosquito eggs is an important transmission channel.[12]

If consumers attribute illnesses caused by bacterial, viral or parasitic infections to malaria, especially as many of these diseases often are self-limiting (meaning that patients recover quickly even in the absence of proper treatment), these misconceptions may hamper learning and induce systematic bias in consumers' beliefs about antimalarial drug quality.

2.2 Supply

Three supply features that are likely to influence the antimalarial drug quality in the market are described below: availability of fake drugs in the supply chain; unobservability of drug quality; and the degree of competition among local outlets.

2.2.1 Availability of fake drugs in the supply chain

Several studies have attempted to quantify the extent of counterfeit and substandard antimalarial medicines over the last few years. A recent meta-analysis of surveys from 21 countries in sub-Saharan Africa and seven countries in southeast Asia estimates that 32% of the tested samples failed the quality tests (Narray et al., 2012). There is also evidence indicating that the problem is growing over time (Newton et al., 2011).

Counterfeit and substandard quality is, however, not a problem specific to antimalarial drugs.

[12] Further evidence from Tanzania by Comoro et al. (2003) indicate that false beliefs about malaria also translate into wrong beliefs about proper treatment. They find that a majority of the women in their study failed to identify mosquito bites as the cause of convulsions, a symptom of severe malaria. Instead, many believed that it was caused by evil spirits and thus chose traditional remedies for treatment.

The World Health Organization estimates that the annual earnings from substandard and counterfeit drugs was US$32 billion in 2003 (WHO, 2003), and Bate (2011) estimates that as much as 15% of the global drug supply outside of advanced countries is counterfeit. This figure rises to over 50% in certain markets in parts of Africa and Asia.

The extent of counterfeit and substandard medicines in circulation in Africa is linked to a variety of causes, not at least a de facto largely unregulated pharmaceutical market where non-licensed drugs shops are common. According to WHO (2010), African countries lack the capacity to control the quality, safety and efficacy of the medicines circulating on their markets or passing through their territories. In a study of counterfeit drugs in Nigeria, Erhun et al. (2001) also list vested interests both on the part of the regulatory officials and the counterfeiters as important underlying reasons.

Bate (2011) estimates that the manufacturer cost, including packaging and distribution, of a counterfeit antimalarial; i.e. a drug that has been deliberately and fraudulently mislabeled with respect to identity and/or source, is about 10% of an authentic drug. The manufacturer cost of substandard drugs, i.e. a drug that is produced by the authorized manufacturer but do not meet quality specifications set for them by national standards, are half to two thirds of those of a high quality manufacturer. A decrease in costs can be achieved by using lower quality ingredients, under-dosing ingredients, cutting the processing time, or lowering hygiene controls.

For an individual drug store, cheating can occur through several ways. First, the seller can buy pre-packaged counterfeit, or substandard, ACT from either the counterfeiter or from wholesalers involved in the distribution of fake drugs. India, China, Nigeria and Pakistan have been listed as the main source countries of poor quality ACTs (Lybecker, 2004). Anecdotal evidence also suggests that repackaging of non-ACTs into ACT blister packages or ACT packs takes place in-country. The seller can also mix non-ACT drugs or poor quality ACTs into ACT packages in the store.

2.2.2 Unobservability of drug quality

The quality of an ACT drug is difficult to distinguish based on visual characteristics as evident from figure 1, which depicts two packs and blister packages from two samples of ACTs purchased and tested in our study: one fake and one authentic. More systematic evidence is presented in Dondorp et al. (2004). They compare counterfeit ACTs purchased in Southeast Asia in 1999 and 2003 and conclude that while most counterfeits sampled in 1999 could be identified by the hologram sticker, most fake samples in the 2003 study had a hologram on the blister pack that was almost indistinguishable from the real product. Newton et al. (2011) conduct a blind study of the physical appearance and text on packaging of counterfeit and substandard antimalarials from eight sub-Saharan African countries, compared with known authentic samples, and conclude that

the packaging of counterfeit drugs is very similar to that of genuine samples.

A strand of the theoretical literature on product quality suggests that, in equilibrium, even though product quality cannot be directly observed ex ante, the price will be higher for high-quality products (Shapiro, 1982; Wolinsky, 1983; Milgrom and Roberts, 1986).[13] Empirically, however, there is scant evidence on the relationship between quality and price in the pharmaceutical market of developing countries. Bate et al. (2011) is an exception. Using data for several drugs collected from 185 private pharmacies across 17 developing and mid-income countries, they reject the hypothesis that price is a monotone function of quality. Although drugs that fail quality tests are priced slightly lower on average, the price dispersion is so large that consumers cannot ensure the purchase of high quality by high price alone.

2.2.3 Competition among local outlets

There is a lack of data on the degree of competition in local drug markets for most developing countries. Data collected in this paper, however, shows that the market in rural areas is usually characterized by low competition, with 55% of local markets (villages) served by a local monopoly. The private providers are also typically small and often unlicensed.

3 Data

The intervention comprised 99 rural villages (local councils) in four districts (Bushenji, Mbale, Mbarara, and Mpigi) in Uganda with high and endemic *P. falciparum* malaria prevalence (figure 2).

We combine a cross-sectional dataset on drug quality with two rounds of household survey data. First, we conducted a census of drug outlets and households in the 99 project villages. We then collected baseline household survey data in all villages in the first half of 2010, followed by a drug quality survey at the end of 2010, about 7-9 months after the intervention had begun. A follow-up household survey was conducted in the fall of 2011 in a subset of 48 randomly selected project villages.

The measurement of drug quality has two main components: the purchase of ACT medicine and testing thereof. For the former, we trained a set of enumerators with knowledge of the local area and language on how to use a prepared script when approaching the outlet. According to the script, the covert shopper was buying medicine for his/her sick uncle. The covert shopper

[13] In Metrick and Zeckhauser (1999) and Akerlof (1970), on the other hand, equilibrium prices do not signal quality differences.

described the age of the uncle (48), symptoms common for malaria, and that he/she wished to purchase Coartem. Although Coartem is an ACT brand name, the term is commonly used for artemisinin-based combination therapy drugs. If the outlet offered multiple brands of equivalent active ingredients and strength, the covert shopper was trained to acquire the least expensive brand. After the purchase was completed, the surveyor recorded the price once out of sight of the outlet owner. The samples were then transferred to Kampala. To prevent deterioration, we followed standard procedures and kept the drugs away from light in a dry and cool place. We purchased ACT drugs from all private outlets that sold ACT in the 99 villages. In total, 559 pills from 94 outlets in 47 villages were purchased.

Chemical analyses of medicines like ACTs can be performed using several techniques.[14] Our method of quality testing was Raman spectroscopy, using a TruScan handheld scanner. In the TruScan scanner, each sample (pill) is illuminated with a laser beam and the reflecting Raman spectra is measured. The Raman spectra provides a fingerprint by which the molecule composition of the sample can be identified. The fingerprint is then tested against an authentic reference sample and if they are sufficiently similar, as given by a probabilistic algorithm, the sample passes the test and is considered authentic.[15] Figure 3 depicts an example of the Raman spectrum of a tested sample. As scanning a tablet takes only about a minute, an important advantage of Raman spectroscopy compared to laboratory methods is speed. Another important advantage is that compared to laboratory testing, which requires a fairly large set of pills to test, and thus would require either multiple purchases or purchase of more than one dose of tablets, the TruScan method provides a quality indicator per tested tablet. Methods comparing Raman spectroscopy to traditional laboratory methods have found a high degree of consistency across methods, and the Raman method is therefore viewed as suitable when conducting field studies (Bate et al, 2009).[16]

To investigate whether one can distinguish fake and authentic drugs based on visually observable characteristics (such as the color and size of the box, blister pack and pills; type of paper cardboard used for the box, characteristics of the text on the box and blister pack, type and presence of holograms, etc.), ten surveyors visually inspected each sample and made an assessment of whether they believed the drugs were fake or not. Individual samples were sequentially presented (without any additional information), and the inspectors' assessments were reported after each sample.

To measure households' beliefs about antimalarial quality in the drug shops, we asked each

[14] See for example Nayyar et al. (2012).

[15] The reference ACT pills used were tested and authenticated through laboratory testing by Chemiphar Laboratory (www.chemiphar.com).

[16] Nine out of the ten largest pharmaceutical companies worldwide rely on Raman spectroscopy technology to authenticate inputs. Moreover, a growing number of national drug enforcement agencies, for example the National Agency for food and Drug Administration and Control in Nigeria (NAFDAC), use the TruScan Raman Spectrometer to test for counterfeit and substandard medicines.

respondent "Do you expect that the antimalarial medicines sold by the nearest drug shop are fake?". A likert scale with four categories was provided, ranging from "no, none of them", via "yes, a few of them", "yes, most of them", or "yes, all of them". Following the medical anthropology literature, we also asked respondents about their beliefs about malaria transmissions. This included whether malaria could be spread from: (1) Direct contact with someone who has malaria; (2) Mosquito bites; (3) Contaminated drinking water; (4) Eating "infected mangos". Since mosquito bites are the biological vectors through which malaria is transmitted, only (2) is true and three of the four statements are thus false.

To measure demand and treatment behavior, we asked about treatment of children reported sick with malaria in the last month, including the source of the medicine, type of antimalarial drug bought, and number of tablets acquired.

3.1 Experimental Design

The experiment is part of a long-run impact evaluation of a market-based community health care program in Uganda. The evaluation is done in a large set of villages (or clusters), organized into 10 branches, of which seven branches are managed by BRAC and three are managed by Living Goods.[17] For the experimental design, the participating villages were first stratified by location (branch) and then by population size. From each group, half of the units were randomly assigned to the treatment group and the remaining units were assigned to the control group.

For the drug quality study in this paper, three BRAC branches and the largest of the three Living Goods' branches were selected. Altogether 99 villages were thus included, of which 48 [51] were treatment [control] sites.

Once the treatment status was assigned, the collaborating NGOs (Living Goods and BRAC) recruited and trained a woman in each village, a Community Health promoter (CHP), to act as the sales agents for Living Goods and BRAC. The CHP:s work under an implicit piece-rate scheme. They are able to purchase authentic ACT antimalarials from the NGO at wholesale price about 40 percent below the market price. The NGO, however, sets the retail price with a target of keeping it approximately 20-30 percent lower than the prevailing local market price.[18] The CHP keeps the difference.

The CHP is expected to sell the ACTs to households in the village to which she is assigned.

[17] Living Goods is an American NGO with a branch in Uganda. They operate networks of independent entrepreneurs who sell treatment and preventive medicines, as well as other health products, mostly in rural areas. In Uganda they work both independently and in collaboration with BRAC-Uganda. BRAC operates a number of different programs across several developing countries with a focus on poverty alleviation.

[18] As the NGOs do bulk purchasing, and have a streamlined distribution system, it can sell products with profits at a significantly lower price than most small-scale drug shops.

She is not allowed to sell directly to other outlets. The NGOs use a combination of monitoring by local branch managers and harsh punishment (dismissal) to ensure that the rules are not broken. Importantly, the CHP carries an ACT brand (Lumartem) that is not sold in local drug shops. This enables us to rule out mechanical effects on market quality from the CHPs selling directly to the outlets. The CHP also has access to other products she can sell, including hygiene products as well as other health products such as deworming pills and painkillers. When interpreting the treatment effect, this should therefore be kept in mind.[19]

Due to the random assignment, there should be no systematic difference between the treatment and the control group. Table 1 reports mean pre-treatment characteristics for both groups and test statistics for equality of the means. Overall the sample is balanced, with only radio ownership being statistically significant at the 10 percent level. We cannot reject the null hypothesis that all differences are equal to zero.

At baseline, 51% of the villages in the treatment group and 60% of the villages in the control group had at least one drug outlet within the village boundaries. Among the village markets, a majority (55 percent) has only one outlet selling ACTs and in 75 percent of the villages there is either a local monopoly or duopoly.

Malaria morbidity among children under 5, here defined as share of children reported to have been sick with malaria in the last month, is 38 percent (39 percent in the treatment group). 45 percent (46 percent in the treatment group) of these children were reported to have been treated with ACT:s.

3.2 Summary statistics

Prevalence of fake drugs

How common are counterfeit and substandard ACTs? Table 2 provides summary statistics of the prevalence of fake drugs in the control group. 36.8% of the outlets sell fake ACT:s. The prevalence is highest in the western, and most rural, districts (Bushenyi and Mbarara), while the prevalence is lowest in the district closest to the capital Kampala (Mpigi). Overall, 19.4% of all drugs fail the authenticity test. This number, however, includes data from outlets where all the tested samples pass the test. When conditioning the sample on outlets where at least one sample (pill) failed the authenticity test, 51.5% of the tested ACT drugs fail.[20]

[19] Since it is unclear why the sale of hygiene products or deworming pills would affect the quality of ACT antimalarials in drug outlets, or household beliefs about the quality of ACTs in incumbent outlets, we believe that it is unlikely that this has a first-order effect on these outcomes.

[20] It is plausible that our results in table 2 provide a lower bound since the covert shoppers were asked to purchase a package of ACTs. Buying less than a full dose of ACTs when seeking treatment is a common practice. As the patient or caregiver will then have to judge the quality by only observing the blister package or single tablets, cheating should become easier.

The last rows in table 2 report data on the prevalence of fake ACTs conditional on the market structure in the villages. In both villages with a monopoly seller and in villages with more than one drug store in the village market, fake ACT:s are common.

Households' expectations of fake drugs

Are households aware that fake drugs are sold? Figure 4 plots the histogram and kernel density of the fraction of households, collapsed at the village level, that report that they believe the nearest drug shop in the village sells (at least some) fake drugs. In the median village 27 percent of households believe the nearest drug shop sells fake drugs. There is also substantial variation in beliefs across villages.

Figure 5 shows how households' beliefs about drug quality correspond to actual quality in drugs shops in villages.[21] As is evident from the figure, when households suspect a high prevalence of fake drugs in the nearest drug shop, the prevalence of fake drugs is indeed higher. Figure 6 shows that there is substantial variation in beliefs across districts. In the district with the lowest prevalence of fake drugs (Mpigi), 18 percent of households believe that fake drugs are sold, while in the district with the highest prevalence (Mbarara), 49 percent believe so. This indicates that consumers are at least partially able to observe or infer quality. However, beliefs are far from perfect. For example, among households that believe that the nearest drug shop does not sell fake drugs, 16 percent of the drugs sold in their villages are, on average, fake (figure 4). Also, the predictive power of beliefs is low, as the r-squared of a simple bivariate regression of actual quality on beliefs shows that that only about one percent of the variation in quality can be explained by household expectations (results not shown for brevity). These facts suggest that some inference of quality is possible, but that quality is difficult to observe and that inference is very noisy for consumers.

Observability of drug quality

Do differences in prices or in observable characteristics like blister packages signal quality differences? Using data on purchased samples from drugs shops, table 3 presents results on the relationship between price and quality in the control villages. By using village fixed effects, we exploit variation across drug shops within the same local market, thereby essentially holding demand (e.g., malaria prevalence, income, and expectations of quality in the village) and supply factors (e.g., transportation costs and degree of competition in the village) constant within a local market. Column 1 shows the correlation from a bivariate regression using a dummy variable indicating whether the outlets sells some fake drugs (1) or not (0), while column 2 uses the share of drugs that are fake.[22] It is evident that variation in prices within a given local market does not

[21] We exclude treatment villages in figure 5 since drug quality is measured after the intervention had begun.

[22] We cluster the standard errors at the village level since drug shops' price and quality choices are likely to be correlated in the village. There are 27 control villages in the sample. The results are robust when using robust standard errors.

signal differences in quality.

Columns 3 and 4 use the data from the visual inspections of the samples. Ten surveyors visually inspected each sample and made an assessment of whether they believed the drugs were fake or not. To set prior beliefs in a manner approximately consistent with the data, the inspectors were informed that thirty percent of the samples were fake. There is little evidence that observable characteristics can reveal quality. While the coefficients are positive, the point estimates are small and not statistically significant at conventional levels, indicating that it is difficult to infer quality solely based on observable characteristics of the products.

Misconceptions about malaria

Figure 7 plots the histogram of households' beliefs about what causes malaria. Essentially all of the respondents (99 percent) correctly answer that malaria can be caused by mosquito bites. However, over 50 percent of the respondents also report that malaria can be caused by direct contact with someone who is infected with malaria. Moreover, 60 percent and over 85 percent of the respondents believe that drinking contaminated water and eating "infected mangos", respectively, can cause malaria.

To capture the degree of misconceptions about malaria transmission, we create a dummy variable indicating a "naive" consumer, defined by whether the respondent answers falsely on three of the four questions. Figure 8 plots the histogram and kernel density of the fraction of "naive" consumers, collapsed at the village level. In the median village, 35 percent of respondents are labeled as naive, and there is substantial variation in misconceptions across villages.

4 A Model of a Local Drug Market

In this section we present a simple model of a local drug market where an outlet's key rationale for selling unobserved high quality drugs is to maintain a good reputation among consumers. The purpose of the model is to understand how drug quality is determined when, as suggested by the evidence presented in sections 2 and 3, consumers do not know whether they have malaria or some other febrile disease; when consumers cannot observe whether the antimalarial drug they buy is authentic or not as neither price differences nor other observable characteristics signal differences in quality; and when (some) consumers with misconceptions incorrectly attribute illnesses caused by bacterial, viral or parasitic infections to malaria.

We first solve the model in the case where there is a local monopoly in the market (the control group outcome). To understand whether good products can drive out bad we then extend the model and introduce a competitor – an NGO – which is committed to selling to high quality

antimalarials at subsidized prices (the treatment group outcome). In both scenarios, our focus is on the incumbent seller's profit-maximizing choice of quality and price.

4.1 Setup

There are two players in the model: drug stores and a continuum of atomistic consumers with measure one. There are two periods. In each period t, a share θ_t of the consumers contracts malaria and a share ω_t of consumers contracts some other self-limiting febrile disease.[23] The share of consumers with malaria, θ_t, is a random variable with *CDF* $F_\theta(\theta)$, distributed on the unit interval.[24]

A consumer recovers quickly if she suffers from malaria and if she is treated with an authentic (high quality) antimalarial. Let m_t denote the share of authentic (high quality) antimalarials sold by the drug store in period t. Then a share

$$\sigma_t = \theta_t m_t + \omega \tag{1}$$

of the consumers that buy antimalarial drugs recovers quickly.

Consumers can be of two types. A share γ of the consumers is assumed to be sophisticated and a share $1-\gamma$ is assumed to be naive. γ is common knowledge. The type of the consumer is denoted with superscript $j = \{s, n\}$. Neither type observes the share of authentic antimalarials sold by the drug store, m_t, nor the malaria shock, θ_t. By observing health outcomes in the village, however, we assume consumers learn (or receive a signal) that at least a share $s(\sigma) \leq \sigma$ of the consumers that bought antimalarial drugs recovered quickly. Consumers know that s is a positive monotone function of σ; i.e. $s'(\sigma) > 0$, but they do not know the functional form of the signal.[25]

Sophisticated consumers observe who buys and uses antimalarial drugs. Sophisticated consumers also know the true distribution of θ and the correct model for σ, i.e. (1). By comparing health outcomes between those that treat their fever with antimalarials and those that do not, they can infer the share of consumers with self-limiting diseases, ω.

Naive consumers make systematic errors regarding malaria. Specifically, naive consumers attribute (self-limiting) illnesses caused by bacterial, viral or parasitic infections to malaria and

[23] Given the informational structure of the game, we can either assume that ω is distributed according to some distribution function $F_\omega(\omega)$, or assume ω is a parameter. For notational simplicity we assume the later.

[24] To simplify the analysis, we assume that all consumers fall sick in each period, implying that $\omega > 0$ if $\theta < 1$ and that a share $1 - \theta_t - \omega_t \geq 0$ contracts a disease which is not self-limiting (in the short run).

[25] The assumption of a postive monotone (but unknown by consumers) relationship between s and σ greatly simplifies the analysis as consumers can then solve their inference problem based on conditional probabilities rather than conditional densities.

thus assume that the share of consumers that recover quickly is generated by the incorrect model

$$\sigma_t' = \theta_t m_t \ . \tag{2}$$

The belief that various self-limiting illnesses are malaria is inconsistent with observed outcomes: a share ω of the untreated consumers recover quickly, implying that – contrary to naive consumers' beliefs – some consumers suffer from self-limiting illnesses. We therefore assume that naive consumers do not make relative comparisons, either across consumers that buy or do not buy antimalarial drugs or across consumers who buy from different outlets.

A consumer that recovers quickly receives a utility-gain κ (in monetary terms). Facing fever, and thus potentially malaria, consumers have two options. They can buy antimalarial drugs of uncertain quality from the drug shop at a price p, or they can search for an alternative provider (e.g. public health clinic or traditional healers) where they can get treatment at no cost. Consumers differ in their ability to search for alternative treatment, or differ in their assessment whether such a search will be successful, implying that the likelihood of receiving effective treatment from an alternative provider is φ^i, where φ^i is assumed to be distributed in the population according to a uniform distribution over the unit interval.[26] We further assume that consumers face a cash constraint, implying that the highest price they can pay for the drug is $p = 1$. Let ρ_t^j denote the expected quality of the antimalarial drug as viewed at the beginning of period t by a consumer of type $j = \{s, n\}$. Then consumer i of type j at time t will buy the drug provided that

$$\hat{\theta}^j \rho_t^j \kappa - p_t \geq \hat{\theta}^j \varphi_t^i \kappa \tag{3}$$

where $\hat{\theta}^j$ is the unconditional probability that the consumer suffers from malaria as perceived by type j.

If the expected net gain of buying antimalarials from the drugs store, $\hat{\theta}\rho\kappa - p$, is higher than the expected gain from searching for an alternative provider, $\hat{\theta}\varphi^i\kappa$, consumer i will buy antimalarials from the drug seller. Thus, demand from consumers of type j in period t, q_t^j, is

$$q_t^j = \rho_t^j - \frac{p_t}{\kappa\hat{\theta}^j} \ \text{ for } \ j = \{s, n\} \tag{4}$$

There are two types of drug shop owners: honest H and opportunistic O, with $T = \{H, O\}$.

[26] As discussed in section 2, the uncertainty can arise because public health clinics in rural Africa are characterized by high rate of absenteeism and stock-outs. Thus, even though drugs should be available for free, the patient faces uncertainty ex ante whether she will receive treatment or not if visiting the clinic.

Nature draws the type at the start of period 1. With probability μ_H the seller is honest and with probability $1-\mu_H$ the seller is opportunistic. Without loss of generality, let $\mu_H = 1/2$. An honest seller sets $m = 1$ while an opportunistic seller sets $m \in [0,1]$. Sellers know their type. Consumers know that $\mu_H = 1/2$. Sellers also observe θ_t before deciding on price and quality in period t and that the signal s is a positive function of σ.[27]

An opportunistic drug shop is assumed to maximize profits,

$$\pi = (p_1 - cm_1) \times q_1 + (p_2 - cm_2) \times q_2 \tag{5}$$

where $q_t = \gamma q_t^s + (1-\gamma) q_t^n$ is period t demand, by deciding the share of authentic (high quality) antimalarials to sell m_t, with $m_t \in [0,1]$, and the prices of the drug, p_t. The cost of selling a share m_t of high quality drugs is cm_t, with $c > 0$.

The timing of the game is illustrated below.

Timing of the game

period 1 → time

nature draws type and θ_1	drug store sets m_1, p_1	consumers decide whether to buy from the local drug store	health outcomes σ_1 is revealed

period 2 → time

nature draws θ_2	drug store sets m_2, p_2	consumers decide, based on s, whether to buy from the local drug	health outcomes σ_2 is revealed

4.1.1 Solution: The Monopoly Case

The solution concept is PBE. Denote the consumers' beliefs or estimate of the sellers' quality choice in period 1 conditional on the type of seller T as $\tilde{m}^T$.

We solve the problem working backwards. Consider first the consumers' choice whether to buy antimalarial drugs or not from the drug store in period 2. The consumers realize that only honest types will sell authentic drugs in last period as the seller's choice of m_2 has no effect on demand or revenue but raises costs. Thus consumers face the problem of determining the likelihood that the

[27] All results continue to hold if assume sellers cannot observe θ_t when deciding p_t and m_t. As introducing uncertainty (for the seller) does not yield additional insights, however, we assume sellers at t can observe θ_t.

seller is honest, given the signal s', and given their beliefs about the sellers' quality choices, $\tilde{m}^T$. That is,

$$\rho_2 \equiv \Pr(H|\sigma \geq s') = \frac{\Pr(\sigma \geq s'|H)\Pr(H)}{\Pr(\sigma \geq s'|H)P(H) + P(\sigma \geq s'|O)P(O)}. \tag{6}$$

Note that ρ_2 is also the expected quality in period 2, as viewed by consumers in the end of period 1. Solving (6) for sophisticated and naive consumers, respectively, yields $\rho_2^s(m_1)$ and $\rho_2^n(m_1)$.[28]

Quantity demanded in period 2, q_2, is then

$$q_2(\theta_1, m_1, p_2) = \gamma \times \left(\rho_2^s(m_1) - \frac{p_2}{\kappa\hat{\theta}^s}\right) + (1-\gamma) \times \left(\rho_2^n(m_1) - \frac{p_2}{\kappa\hat{\theta}^n}\right). \tag{7}$$

Consider now the problem facing the consumers in period 1 when making their first potential purchase without having received a signal about σ. Then the expected quality of the medicine, as perceived by the consumers, is the same for both types of consumers and given by $\rho_1 = \mu_H + \mu_O\tilde{m}_a^O$. The quantity demanded in period 1, q_1, is thus

$$q_1(p_1) = \rho_1 - \gamma\frac{p_1}{\kappa\hat{\theta}^s} - (1-\gamma)\frac{p_1}{\kappa\hat{\theta}^n} \tag{8}$$

Consider finally the opportunistic seller's maximization problem in period 1. The seller will choose m_1, p_1, and p_2 so as to maximize profits, given in (9), taking consumers' beliefs and strategies as given,

$$\max_{\{m_1,p_1,p_2\}} \; p_1 \times q_1(p_1) + p_2 \times E_{\theta_1}\left[q_2(\theta_1, m_1, p_2)\right] - cm_1. \tag{9}$$

Let m^* denote the equilibrium share of authentic (high quality) antimalarials sold in period 1 by an opportunistic seller. We then have the following proposition.[29]

Proposition 1: *There exist an equilibrium in which* (A) *The opportunistic seller will sell at least*

[28]Note that for sophisticated consumers $\Pr(\sigma \geq s'|T) = 1 - \Pr(\sigma \leq s'|T) = 1 - \Pr\left[\theta \leq (s'-\omega)\tilde{m}^T\right] = 1 - F_\theta\left((s'-\omega)/\tilde{m}^T\right)$. For naive consumers we have $\Pr(\sigma \geq s'|T) = 1 - F_\theta\left(s'/\tilde{m}^T\right)$. Thus

$$\rho_2^s(m_1) = \frac{1 - F_\theta\left(\frac{s'-\omega}{\tilde{m}^H}\right)}{1 - F_\theta\left(\frac{s'-\omega}{\tilde{m}^H}\right) + 1 - F_\theta\left(\frac{s'-\omega}{\tilde{m}^O}\right)}; \; \rho_2^n(m_1) = \frac{1 - F_\theta\left(\frac{s'}{\tilde{m}^H}\right)}{1 - F_\theta\left(\frac{s'}{\tilde{m}^H}\right) + 1 - F_\theta\left(\frac{s'}{\tilde{m}^O}\right)}$$

[29]The proofs of the propositions are in the appendix.

some fake drugs in period 1; i.e. $m^* < 1$. (B) *Conditional on actual quality* m^**, naive consumers expect fewer fake drugs and overestimate quality; i.e.,* $\rho^n > \rho^s$. (C) *The higher the share of naive consumers, the lower the share of authentic drugs in equilibrium; i.e.,* $\partial m/\partial\gamma > 0$*. (D) Provided that the utility-gain* κ *of recovering quickly is sufficiently large, the cash-constraint binds, implying that the price is constant and equal to one in both periods; i.e.,* $p_t = 1$.

The opportunistic seller weighs the marginal benefit of increasing drug quality in period 1, which raises consumers' expectations about drug quality, $\partial\rho_2/\partial m$, and thus demand in period 2, against the marginal cost, c.

When receiving a signal about the share of people who recovered after treatment, naive consumers mistakenly assume that everyone had malaria and recovered because they received authentic antimalarial drugs. In reality, there is a share ω that had a self-limiting disease and recovered regardless of drug quality. Consequently, naive consumers infer a higher drug quality from their signal than sophisticated consumers; i.e., $\rho_2^n > \rho_2^s$. Moreover, the failure to attribute self-limiting illnesses to malaria implies that the signal carries less information and therefore that an increase in m, and thus a higher signal s', results in a smaller upward revisions in naive consumers' expectations about drug quality as compared to sophisticated consumers; i.e., $\partial\rho_2^n/\partial m < \partial\rho_2^s/\partial m$. As a result, the higher the share of naive consumers, $1-\gamma$, the lower the seller's weighted marginal return to higher quality, $\gamma\partial\rho_2^s/\partial m + (1-\gamma)\partial\rho_2^n/\partial m$, and the lower the equilibrium choice of m. That is, $\partial m/\partial\gamma > 0$.

The cash-constraint binds provided that marginal revenue, $\partial pq(p)/\partial p$, is increasing in p at $p = 1$ and $m = m^*$. This will be the case if the utility-gain κ of recovering quickly is sufficiently large.

4.1.2 Entry by a Seller Committed to High Quality

Consider now an extension of the model with an additional outlet that is committed to selling high quality antimalarials. That is, let the seller be an honest type. Given the empirical setting in this paper, we label the entrant an NGO. In principle, however, the seller could of course be a government-owned outlet committed to high quality.

Consumers cannot directly observe the type of either seller.[30] As our focus is on how the incumbent reacts to competition of a high quality seller, we take the NGO:s actions as given and simply postulate, consistent with the intervention discussed in section 3, that it sets a price $p_{NGO} < 1$ and $m_{NGO} = 1$.

[30]To keep the model simple, we assume the incumbent seller can observe the type of the NGO. However, the results hold in a more general model where the sellers only know the proportions μ_H and μ_O.

Given the assumption that the malaria shock is common across the village, with two sellers on the market, sophisticated consumers are provided with information they can use to determine relative quality of the drugs, and thus possibly the sellers' type. Specifically, relative signals about health outcomes are

$$s_I / s_{NGO} = (m_I\theta + \omega) \,/\, (m_{NGO}\theta + \omega)\,, \tag{10}$$

where subscript I denotes the incumbent seller. If $s_I/s_{NGO} < 1$, sophisticated consumers can conclude that $m_I < m_{NGO}$ and since honest types by assumption choose $m = 1$, that the incumbent seller cannot be an honest type.[31]

With the entry of the NGO, the problem for the opportunistic seller is now reduced to a choice of either setting a $m_I \in [0,1)$ in period 1 such that only (a fraction of) naive consumers are willing to buy or set $m_I = 1$ and cater to both types of consumers.[32]

Assumption A1: $\frac{1}{2} p_{NGO} \left[\frac{1}{2} - \frac{p_{NGO}}{\kappa\hat{\theta}^s}\right] > c$

Proposition 2: *If conditions A1 hold, and if the share of naive consumers is sufficiently low, the opportunistic seller sets* $m = m_I^* = 1$ *in period 1 and charge a price* $p_I^* = p_{NGO}$.

Proposition 3: *If conditions A1 hold, and if the share of naive consumers is sufficiently high, the opportunistic seller sets* $m = m_I^{**}$ *in period 1 and charge a price* $p_I^* = p_{NGO}$. *The equilibrium drug quality* m_I^{**} *is lower than in the monopoly case; i.e.* $m_I^{**} < m^* < 1$.

With the NGO on the market, sophisticated consumers can distinguish the quality choice from the health shock. As the NGO sets $m_{NGO} = 1$, by assumption, the incumbent seller must mimic the NGO and also set $m = 1$ to ensure that sophisticated consumers buy in the future. Such a strategy is optimal provided that reputational concerns are sufficiently important. Reputational concerns are important if the share of naive consumers is not too large (as naive consumers are assumed not to make inferences based on relative health outcomes), and provided that the gain from reputation; i.e., higher period 2 revenues (the left-hand side of A1) outweighs the reduction in costs from deviating and setting $m_1 = 0$ (the right-hand side of A1). Furthermore, as the NGO sets the price $p = p_{NGO} < 1$, the incumbent seller will be forced to set the same price in order to avoid losing customers.

With a sufficiently large share of naive consumers in the market, on the other hand, the incumbent seller no longer mimics the NGO. The equilibrium drug quality m_I^{**} is lower than in the

[31] As discussed above, naive consumers are assumed not to use this additional information to assess the sellers' type.

[32] If both sellers charge the same price for the same expected quality, consumers are indifferent and randomly pick one of the sellers to buy from.

monopoly case for two reasons. First, as the marginal return of higher quality is lower for naive consumers as compared to sophisticated ones for all $m < 1$, the seller's marginal return schedule is shifted inward when the market place is dominated by naive consumers, and as a consequence equilibrium quality falls. Second, as $p_{NGO} < 1$ and half of the (naive) consumers now choose to buy their drugs from the NGO, the marginal return falls for all m, thus equilibrium quality falls.

4.2 Discussion: Assumptions and Predictions

In the following sections we use the model as motivation to identify and assess a set of hypotheses on how quality is determined in local drug markets. We start in section 6.1 by reporting a set of correlations between prices, actual and perceived beliefs about quality, and consumers' knowledge about malaria and malaria transmissions. We then exploit our experimental design in section 6.2 to test a set of predictions about how the local drug market; i.e., the incumbent seller, reacts to the entry of a new seller - the NGO - selling high quality and subsidized antimalarial medicines.

Below we discuss the main predictions of the model.

1. Expectations of quality and quantity demanded. Although drug quality is not directly observable, consumers may partially infer quality based on health outcomes. As authentic drugs are more valuable, quantity demanded conditional on health outcomes, quality and price in the local market (i.e., period 2), is increasing in expected quality: $\partial q(\rho;\theta,m,p)/\partial\rho > 0$.

2. Misconceptions about malaria and quality. Naive consumers with misconceptions about malaria make systematic errors regarding the relationship between health outcomes and drug quality. Specifically, they do not realize, or do not take into account, that a share ω of consumers get fever due to other, self-limiting, infections. Therefore, conditional on actual quality m^*, naive consumers expect fewer fake drugs and overestimate quality,

$$\textbf{2a)} \text{ Conditional on } m^*,\ \rho^n > \rho^s.$$

As a consequence, the marginal gain of selling authentic drugs falls when there are many naive consumers in the market. As the share of naive consumers increases, more fake drugs will be sold by the drug shop in equilibrium,

$$\textbf{2b)}\ \frac{dm}{d\gamma} > 0.$$

3. Treatment effect: Quality. When the NGO enters and starts selling authentic drugs, the share of authentic drugs sold by the incumbent outlet increases, provided that the share of naive consumers is not too high. Intuitively, with the NGO on the market, sophisticated consumers can

assess relative quality from relative health outcomes. In order not to be revealed as an opportunistic type, and thus lose future demand, the incumbent outlet needs to mimic the new entrant's quality choice; i.e. it needs to raise quality,

$$m_I^* > m^*$$

4. Treatment effect: Price. In order not to lose customers, the incumbent seller will be forced to lower its price when facing competition from a high quality, low price seller.

5. Treatment effect: Quantity and expectations of quality. With the NGO on the market, equilibrium quantity will *increase*. This is due to two mechanisms. First, since consumers expect more authentic drugs overall in the market, the demand curve shifts outward. Second, a lower price leads to movement along the demand curve.

6. Heterogeneous treatment effects: Misconceptions about malaria. In expectation, the effect of NGO entry on incumbent drug quality is decreasing in the fraction of naive consumers, $1-\gamma$. Intuitively, the strategy to mimic the new entrant's quality choice; i.e. to raise quality, is optimal provided that the share of naive consumers is not too large. The higher the share of naive consumers, the more likely it is that the incumbent seller will switch strategy and only cater for the naive market segment. As the return to quality falls in the share of naive consumers, actual quality falls in the share of naive consumers.

5 Empirical Strategy

We combine the household data with the drug quality data. To assess the impact of the intervention, we use OLS to estimate the following specification

$$y_{ovd} = \beta NGO_v + \lambda_d + \gamma X_{vd} + \varepsilon_{ovd}, \tag{11}$$

where y_{ovd} is the outcome of interest (e.g. failed quality test) for outlet o, in village v, of district d. The NGO_v variable is a dummy indicating whether the village is assigned the new CHP worker/outlet. For increased precision and additional robustness, we include village covariates, X_{vd}. This consists of the share of household heads with secondary and tertiary education, the share of households with electricity, television, radio, number of children, Muslim religion, population, and number of drug shops. The randomization was stratified at the district level, hence we include district fixed effects λ_d.

To test whether the fraction of consumers with false beliefs about malaria affect market quality, we run

$$(12) \qquad fake_{ovd} = \beta NGO_v + \theta naive_v + \eta(NGO * naive)_v + \lambda_d + \gamma X_{vd} + \varepsilon_{ovd},$$

where $fake_{ovd}$ is the failed quality test, and $naive_v$ is the village average of the measure of false transmission beliefs. If naive beliefs hamper learning, predictions 2 and 6 imply $\theta > 0$ and $\eta < 0$.

When investigating household beliefs and consumption behavior, we also run regressions either at the household or at the child level (using a sample of children reported sick with malaria during the last month).

6 Results

6.1 Correlations

We first present simple correlations, using household survey data from the baseline survey and data on drug quality from control villages.

Prediction 1. Expectations of quality and quantity demanded

Do consumer beliefs matter? In the model, conditional on actual quality in the market, quantity demanded is increasing in expected quality. Table 4 uses baseline household survey data on beliefs and treatment of under age 5 children reported sick in malaria.[33] To hold health outcomes, price and quality in the local market constant, we exploit variation across households within the same market (village) in the baseline data. Column 1 shows that households that believe that the nearest drug shop in the village sells fake antimalarial drugs are approximately 7 percentage points less likely to treat the child with medicine from private drug shops (the comparison category consists of treatment from public hospitals/health centers, NGOs or other source). The point estimate is essentially the same when including household controls, which suggests that the relationship does not simply reflect income effects or heterogeneity in costs of going to the public health centers. Columns 3-6 investigate whether beliefs about quality are correlated with the likelihood of treating the child with ACT (the extensive margin, columns 3 and 4) and the number of pills conditional on ACT treatment (intensive margin, columns 5 and 6). The estimates show that the likelihood of ACT treatment does not depend on beliefs, but when mothers believe that there are fake antimalarial drugs in the nearest private outlet, children reported sick in malaria are treated with 0.7 fewer

[33] The respondent is the mother of the child. We did not survey treatment behavior among adults.

ACT pills. As the average number of tablets is 6.7, the results in columns 5 and 6 suggest that consumers' beliefs about quality are an important factor determining ACT demand.[34]

Prediction 2. Misconceptions about malaria and quality

As discussed in section 3, there is large variation in beliefs about drug quality across villages. There is also substantial variation within villages in the data. Why do some households expect fake drugs while others do not, even within the same local market? In the model, misconceptions about what causes malaria plays an important role, as "naive" households underestimate the prevalence of fake drugs. More such "naive" households will, in turn, affect drug quality negatively.

Using baseline household survey data, regressions 1-3 of table 5 investigate how misconceptions about malaria are correlated with beliefs about the prevalence of fake drugs. Naive households expect higher drug quality in private outlets, even when holding actual quality constant (through village fixed effects in column 3). The point estimate in column 3 implies that naive consumers are 7.7 percentage points less likely to believe that the nearest outlet sells fake antimalarial drugs. The estimates are similar regardless of whether one controls for education and a set of household wealth variables. This provides suggestive evidence that misconceptions indeed lead to overoptimistic beliefs about quality, and that the relationship does not simply reflect general differences in socioeconomic status.

Furthermore, figure 8 shows that there is substantial variation in misconceptions across local markets. Do drug shops exploit consumers' misconceptions as the model predicts? Using the drug shop data matched with average village beliefs about malaria transmission, regressions 4-8 estimate whether drug quality is associated with the prevalence of misconceptions about malaria in the village. The results show that drug shops are more likely to sell fake drugs in markets where misconceptions are more common. The correlation remains significant when controlling for average education, wealth, market size (number of households), and degree of competition (number of drug shops). A one standard deviation (15.2 percentage points) increase in the share of naive consumers in the market is associated with a 18.6 percentage point higher likelihood that an outlet sells fake drugs (column 5), and a 9.0 percentage point increase in the share of fake drugs sold by drug shops (column 7).

Interpretation

The results discussed above are simple correlations. Interpreted within our theoretical framework, however, they provide suggestive evidence of how the local markets for antimalarial medicine work: fake ACT drugs are common, with substantial spatial variation across local markets. Observable characteristics and prices do not reveal quality, but households are able to partially infer

[34] A full dose of a normal strength Coartem ACT for a child of less than 15 kg bodyweight is 6 tablets, and 12 tablets for 15-25 kg bodyweight.

quality, possibly by observing health outcomes conditional on treatment as in the model. However, consumers' ability to learn appears to be limited, as only a small fraction of the variation in actual quality can be predicted by households' expectations, indicating a noisy information environment. Nevertheless, these beliefs are important, as consumer expectations of drug quality appear to affect demand, even conditional on actual quality in the market.

Moreover, consumers with misconceptions about how malaria is transmitted appear hampered in their ability to infer drug quality, making them systematically more optimistic about quality. The prevalence of consumers with an over-optimistic bias also appears to have consequences for drug quality, as drugs shops sell more fake drugs in markets where misconceptions are more common. This finding is consistent with the hypothesis that low quality is optimal when many consumers are naive, as the reputation forces then are weaker.

In the next section, we investigate the market for antimalarial drugs further by testing predictions 3-6, and present causal evidence on the impact of the intervention on market outcomes.

6.2 Treatment Effects

Can superior products drive out inferior ones?[35] In this section we estimate the effects of entry by the NGO selling authentic ACT drugs on market outcomes. We are test four hypotheses. First, we test whether the intervention improved drug quality among incumbent drug shops. We then assess whether price and quantity were affected. Finally, we investigate whether imperfect consumer learning due to misconceptions about malaria is an important determinant of market quality, as suggested by the previous sections.

Prediction 3. Treatment Effects on Quality

Table 6 shows that the intervention increased quality in incumbent drug shops. Having an NGO outlet in the local market decreased the likelihood that an incumbent drug shop sells fake ACTs by 20-21 percentage points (columns 1 and 2). Columns 3 and 4 show that the share of fake drugs in incumbent drug shops decreased by 11-12 percentage points. From a baseline of 19.4 percent, this implies that the prevalence of fake drugs dropped by more than fifty percent. The intervention therefore had a substantial impact on drug quality by directly providing consumers with authentic drugs, and indirectly through market externalities, by leading to more authentic drugs in the incumbent drug shops.

Recall that the CHP carries an ACT brand (Lumartem) that was not sold in local drug shops at the time of the intervention, thus ruling out a mechanical effect on market quality from the CHPs

[35] Since the NGO sold a high quality product at a lower price the product was superior compared to the existing products on the market.

selling directly to the outlets.[36]

Prediction 4. Treatment Effect on Price

Table 7 estimates the effect on prices and provides evidence consistent with prediction 6. The entry of the NGO resulted in a fall in the average price of ACTs in incumbent drug shops by approximately 18-20 percent (14.6 to 16.5 log points); i.e. from an average baseline price of 8910 Ugandan shillings (in control villages) to approximately 7100-7400 Ugandan shillings in the treatment villages. As the price of ACT sold by the NGO in treatment villages was approximately 7000 Ugandan shillings at the time of the intervention, the difference between the NGO price and the average price among drug shops therefore decreased from about 27 percent to 1-6 percent. Since the intervention led to lower prices and increased quality, it follows that local drug markets were characterized by substantial prevalence of low quality products accompanied with substantial mark-ups.

Prediction 5. Quantity and expectations of quality

Next, we estimate how the intervention affected demand; i.e., the treatment behavior of children reported sick in malaria. Columns 1 and 2, table 8, show there is no statistically significant impact on the likelihood of purchasing medicines from the private drug shops. The likelihood of treating sick children with ACT (extensive margin) was also not affected (columns 3 and 4). However, the intervention affected the intensity of ACT treatment. Conditional on purchasing ACT, households acquired more pills. The effect is substantial. In treatment villages households acquired 2.6 more pills per sick child. From a baseline of 6.7 pills in control villages, this implies a 39 percent increase in ACT quantity. The intervention therefore substantially increased the size of the market for ACTs, consistent with prediction 5.

Do consumers respond by increasing demand because quality is higher, or are the quantity effects simply due to lower prices? The results in columns 1 to 6 of table 8 are consistent with the NGO outlet *shifting* the price-quantity demand curve outward, as consumers respond to higher quality in the market. They are also consistent with movements *along* the demand curve. In the model, both effects are predicted to be present.

A closer look at the estimates suggests that it is unlikely that the quantity effects are driven solely by movements along the demand curve. First, if this was the case, the implied price elasticity of ACT demand would approximately be -2. A priori, this seems implausibly large. Experimental data from rural Kenya by Cohen et al. (2011) also indicates that the price elasticity is much smaller. In fact their results indicate that the demand curve for children is essentially perfectly inelastic, at

[36]A trivial fraction (two percent) of the pills purchased in drug shops in treatment villages were of the brand Lumartem (either due to 'leakage' from the CHP, public clinics, or re-selling by consumers). We also tested ACT quality from samples bought from 10 CHPs. All passed the authenticity test.

least for ACTs that are already highly subsidized.[37]

Second, consumer expectations of drug quality in incumbent drug shops changed. Columns 7 and 8 estimate the treatment effect on expectations of quality. Households in treatment villages are approximately 8 percentage points less likely to believe that the nearest outlet sells fake antimalarials. From a baseline of 34 percent in control villages, this implies that approximately 24 percent fewer households expect fake antimalarials in the treatment villages. This suggests that the increase in quantity is not only due to lower prices in incumbent drug shops, but driven both by lower prices and improved quality.

Prediction 6. Heterogeneous treatment effects: Misconceptions about malaria

According to the model, consumers' ability to learn is a key reason for why incumbent outlets increase drug quality when the NGO enters. If this type of learning is a driver of the externality effects on quality in drug shops, we should expect smaller treatment effects on quality in villages with wide-spread misperceptions about malaria. Table 9 reports estimates of heterogeneous treatment effects; i.e. treatment effects conditional on the prevalence of misconceptions about malaria among households in the village. The interaction term coefficients in columns 1-4 indicate that the effects on drug quality are indeed lower in villages where a large share of the consumers hold false beliefs about what causes malaria. The estimates suggest that when the share of naive consumers is one standard deviation above the mean, there are no improvements in quality when the NGO enters.[38] Together with table 6, these results indicate that misconceptions about malaria influence antimalarial drug quality, as opportunistic drug shops find it more profitable to sell poor quality antimalarials when consumers find it difficult to correctly infer quality.

Interpretation

The intervention introduced an outlet that sold authentic ACT:s at below market prices and, in the majority of treatment villages, changed the market for ACT medicines from a non-competitive (monopolistic) to a competitive environment. The results, therefore, should be interpreted as driven by the combined effect from these, plausibly, complementary factors even though the model highlights specific channels. In the model, for example, the incumbent raises quality in order to maintain his reputation when the new entrant sells high quality medicines and this effect would remain the same had the new entrant sold ACTs at market prices. Thus, viewing the results strictly through the lens of the model, the lower price should have no bearing on the quality results. However, as

[37] For individuals of all ages, their results show that a subsidy of between 80 and 92 percent increases the likelihood of buying ACTs in private drug shop by approximately 32 percent. Also, comparing their results on children with our results is problematic, since they investigate the extensive margin. The most comparable coefficients are therefore those in columns 3 and 4, which are indeed consistent with a perfectly inelastic demand curve at the extensive margin.

[38] Interestingly, when there are sufficiently many naive consumers, the treatment effects on quality become negative. This is predicted by the model, as incumbent outlets will find it profitable to target the naive consumer segment of the market.

we assess a combined effect we cannot rule out that the lower price had an impact on our finding regarding quality. For example, it is possible that the lower price increased the take-up of ACTs which in turn resulted in faster learning about quality than otherwise would have been the case.

Moreover, our results do not speak to the question of whether improved quality or lower prices, holding the degree of competition constant, would change the market outcome. To assess this hypothesis one would need to evaluate the effects from changing the behavior of existing drug stores in the market; i.e. a different intervention then the one we evaluate. We also cannot rule out the effect of competition *per se*, although the data presented in table 2 shows there is no significant relationship between measures of competition and the likelihood that fake drugs are sold. What our results shows, however, is that high quality products, priced competitively, can drive out bad ones even when quality is not directly observable, but that the mechanism appears weaker when consumers are less able to infer quality.

Finally, in the model the incumbent seller knows and sets quality. However, it is possible that the sellers also face uncertainty about the quality they purchase from wholesalers. While we cannot rule out this is the case, the treatment results are difficult to explain without assuming the drug shops have some control over the quality they sell.

7 Discussion

Combining data on direct measures of ACT quality with observational data on market structure and survey data on consumer behavior and beliefs across almost one hundred rural villages in Uganda, we show that the presence of poor quality ACTs is a common problem. Consumers are aware that fake drugs are in circulation and are partly able to infer quality, although authentic and fake drugs are sold at the same price. Building on these facts we lay out a simple model where outlets' key rationale for selling unobserved high quality drugs is to maintain a good reputation among consumers. Using an experimental design, and in the spirit of Akerlof's (1970) discussion of counteracting the market for lemons problem, we study the effects of increased local competition through the entry of a branded high quality seller. We show that the intervention had externalities on incumbent outlets: the entry of high quality sellers decreased the share of fake drugs sold by the incumbents by approximately 50 percent. Motivated by the model, we also shed light on the underlying mechanisms driving this result. Taken together, our results suggest that the prevalence of poor quality antimalarial drugs is partly due to hampered learning about quality arising from misconceptions about malaria.

Understanding how local markets for antimalarial medicines work is of high policy relevance as a key component of malaria control rests on the availability of early treatment with high quality

antimalarial medicines, and as a majority of households in sub-Saharan Africa access antimalarials from the private sector.

An underlying reason for the growing problem of counterfeit and substandard ACTs in Africa is the lack of enforcement of regulations to safe-guard public health; i.e. there is little control of the quality, safety and efficacy of the medicines circulating in the market. While strengthening the regulatory framework and improving enforcement of existing regulations might be the first-best solution, these reforms are not easily implemented in the short run. Our work suggests a number of complementary approaches. First, the results in the paper show that NGOs intervening in private markets not only can have a direct effect on drug quality, but can also change the market equilibrium. Therefore, in the short run, NGOs may provide a partial solution to the public health problem of poor quality drugs. A second, and more suggestive, implication of our findings is that health education addressing poor knowledge and misconceptions about malaria transmission may not only improve the match between illness and treatment, but may also raise drug quality on the market through households' ability to infer quality.

Our findings also suggest avenues for future research. For example, and according to the model, stimulating the demand and use of new diagnostic technologies such as rapid diagnostic tests (RDTs) should reduce the amount of fake antimalarial medicines to the extent that it reduces consumers uncertainty about whether they are suffering from malaria or not. This, in turn, would make it more difficult for sellers to sell low-quality drugs without reputational loss. That is, RDTs may not only reduce overtreatment of malaria but may also improve drug quality. Moreover, anti-malarial drugs form part of a wider set of products where quality is not directly observable at the time of the purchase and only partially observable when used. For example, in many African countries there have been reports of counterfeit and poor quality agricultural inputs such as seeds and fertilizers. Studying such markets is important since poor product quality for inputs can not only directly affect productivity, but also people's willingness to experiment and adopt new technologies. Finally, while counterfeit medicines have traditionally been more of a concern in developing countries, counterfeiting has become more and more prevalent in developed countries as drug supply chains increasingly cross continents through online markets (Lancet, 2012). Identifying effective policies and interventions to deal with the problem of fake drugs in both developing and developed regions is thus an important area for research.

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9 Appendix: Proof of proposition 1-3

Proof of proposition 1: We want to show that there exist an equilibrium in which (A) $m^* < 1$, (B) $\rho^n(m^*) > \rho^s(m^*)$, (C) $\partial m^*/\partial\gamma > 0$, and (D) $p_1^* = p_2^* = 1$.

Assume θ has a truncated normal distribution over the unit interval with mean $\bar{\theta}$ and standard deviation σ_θ. Further let $s = \alpha\sigma$ with $\alpha \approx 1$. Assume the cash-constraint binds implying that the seller will charge the highest price the consumers can pay; i.e. $p_1 = p_2 = 1$. Substituting for s' and maximizing (9) with respect to m_1, yields the first-condition for the optimal share of authentic drugs.

$$\gamma\frac{\partial\rho^s(m)}{\partial m} + (1-\gamma)\frac{\partial\rho^n(m)}{\partial m} - c = 0 \tag{13}$$

In equilibrium, the sellers' quality choices are consistent with the consumers' expectations or beliefs, so $\tilde{m}_a^O = m_1 = m^*$ and $\tilde{m}_a^H = 1$. The first-order condition can then be re-written as

$$\left[\gamma\left[\frac{1}{m^*}h\left(x_1\right) - h\left(x_2\right)\right]\Delta_1^s + (1-\gamma)\left[\frac{1}{m^*}h\left(x_3\right) - h\left(x_4\right)\right]\Delta_1^n\right] - c = 0, \tag{14}$$

where $h(x)$ is the hazard rate, $x_1 = \theta$, $x_2 = \theta m^*$, $x_3 = \theta + \omega/m^*$ and $x_4 = \theta m^* + \omega$, $\Delta_1^s = \frac{\theta[1-F_\theta(x_1)]\times[1-F_\theta(x_2)]}{([1-F_\theta(x_1)]+[1-F_\theta(x_2)])^2}$ and $\Delta_1^n = \frac{\theta([1-F_\theta(x_3)]\times[1-F_\theta(x_4)])}{([1-F_\theta(x_3)]+[1-F_\theta(x_4)])^2}$. Equation (14) implicitly defines the equilibrium share of authentic (high quality) antimalarials m^*. As θ is normally distributed, the hazard rate is increasing in x. As $x_1 \geq x_2$ and $x_3 \geq x_4$, the term in brackets is positive for all $m^* < 1$. As the term in brackets goes to 0 when m^* goes to 1 and $c > 0$, $m^* < 1$.

The second order condition is

$$\gamma\frac{\partial^2\rho^s}{\partial m^2} + (1-\gamma)\frac{\partial^2\rho^n}{\partial m^2} < 0 \text{ at } m = m^* \tag{15}$$

where

$$\partial^2\rho^s/\partial m^2 = -\bar{\theta}^2\left[f'(x_2)\left(1-F(x_1)\right) - f'(x_1)\left(1-F(x_2)\right)/m^*\right] \tag{16}$$

$$\partial^2\rho^n/\partial m^2 = -\bar{\theta}^2\left[f'(x_4)\left(1-F(x_3)\right) - f'(x_4)\left(1-F(x_3)/(m^*)^2\right]\right. \tag{17}$$

The second-order condition may be positive for some realizations of θ. However, at $\theta \approx E_\theta[\theta] =$

$\bar{\theta}$, $\partial^2\rho^s/\partial m^2 < 0$ as $f'(x_1) = f'(\bar{\theta}) = 0$ and $f'(x_2) = f'(\bar{\theta}m^*) > 0$. $\partial^2\rho^n/\partial m^2 < 0$ if $f'(\bar{\theta}m^* + w) > 0$ and $f'(\bar{\theta} + \omega/m^*)$ is small. A sufficient condition for this is that either ω is sufficiently small, or that $\omega < \bar{\theta}(1 - m^*)$ and that the standard deviation of θ, σ_θ, is sufficiently large.

$\rho^n > \rho^s$ at $m = m^*$ if

$$\frac{1 - F_\theta(x_2)}{1 - F_\theta(x_1)} < \frac{1 - F_\theta(x_4)}{1 - F_\theta(x_4) + 1 - F_\theta(x_3)} \tag{18}$$

The left-hand side (LHS) of (18) is equal to the right-hand side (RHS) at $\omega = 0$. The LHS is not a function of ω. The RHS, however, is increasing in ω; i.e. $\partial\text{RHS}/\partial\omega = \frac{1}{m^*}h(x_3) - h(x_4) > 0$. That is $\rho^n > \rho^s$ for $\omega > 0$.

Total differentiating the first-order condition (14) yields

$$\frac{\partial m^*}{\partial \gamma} = \frac{-\left[\partial\rho^s(m^*)/\partial m - \partial\rho^n(m^*)/\partial m\right]}{S.O.C} > 0 \tag{19}$$

As $\partial\rho^s(m^*)/\partial m = \partial\rho^n(m^*)/\partial m$ when $\omega = 0$ and $\partial\rho^n(m^*)/\partial m$ is a decreasing function of ω provided that the second-order condition (17) holds; i.e., $\partial^2\rho^n(m^*)/\partial m\partial\omega = \partial^2\rho^n/\partial m^2 < 0$, the term in the brackets in the numerator is positive for all $m^* < 1$ and $\omega > 0$.

The cash-constraint binds provided that the marginal return is increasing in p at $p = 1$ and $m = m^*$; i.e., if

$$\partial p_1 q_1(1)/\partial p_1 = \rho_1(m^*) - 2\left[\frac{\gamma}{\hat{\theta}^s} - \frac{(1-\gamma)}{\hat{\theta}^n}\right]\frac{1}{\kappa} > 0 \tag{20}$$

$$\partial p_2 q_2(\theta_1, m_1, 1)/\partial p_2 = \gamma\left[\rho_2^s(m^*) - \frac{2\gamma}{\hat{\theta}^s}\frac{1}{\kappa}\right] + (1-\gamma)\left[\rho_2^n(m^*) - \frac{2(1-\gamma)}{\hat{\theta}^n}\frac{1}{\kappa}\right] > 0 \tag{21}$$

which is the case if the utility-gain κ of recovering quickly is sufficiently large.

Proof of proposition 2: As $\gamma \to 1$, the opportunistic seller's only relevant options are to set $m_1 = 1$ or $m_1 = 0$. Setting a $m > 0$ (but < 1) would raise costs but have no effect on future demand as the seller would be revealed as not being honest. Consider the case where the incumbent seller sets $m_1 = 1$. Further, let $\tilde{m}_I^O = \tilde{m}_{NGO}^O = 1$, $\tilde{m}_I^H = \tilde{m}_{NGO}^H = 1$, and $\tilde{m}_I^D = \tilde{m}_{NGO}^D = 0$. The NGO is an honest type and is assumed to set the price $p_{NGO} < 1$. Note first that to avoid

losing customers, the incumbent seller is forced to set the same price as the NGO; i.e. $p^* = p_{NGO}$. The incumbent seller's expected profits, $E[\pi]$, is then

$$E\left[\pi | m = 1, \tilde{m}_a^O = 1\right] = p_I^* \times \frac{1}{2}\left[1 - \frac{p_I^*}{\kappa\hat{\theta}^s}\right] + p_I^* \frac{1}{2}\left[\frac{1}{2} - \frac{p_I^*}{\kappa\hat{\theta}^s}\right] - c \tag{22}$$

Deviating and choosing $m = 0$ yields expected profits

$$E\left[\pi | m = 0, \tilde{m}_a^O = 1\right] = p_I^* \times \frac{1}{2}\left[1 - \frac{p_I^*}{\kappa\hat{\theta}^s}\right] \tag{23}$$

Comparing expected profits, equations (22) and (23), yields condition A3.

Proof of proposition 3: Consider the alternative scenario when $\gamma \to 0$. Then the seller only caters to naive consumers. Let $\tilde{m}_I^O = \tilde{m}_{NGO}^O = \tilde{m}^O$, and $\tilde{m}_I^H = \tilde{m}_{NGO}^H = 1$. The seller's maximization program is

$$\max_{m_1} \; p_I^* \frac{1}{2}\left(\rho_1^n - \frac{p_I^*}{\kappa\hat{\theta}^n}\right) + p_I^* \frac{1}{2}\left[\rho_2^n(m_1) - \frac{p_I^*}{\kappa\hat{\theta}^n}\right] - cm \tag{24}$$

Maximizing (24) with respect to m_1, yields the first-condition for the optimal share of authentic drugs. In equilibrium, the sellers' quality choices are consistent with the consumers' expectations or beliefs. Thus, the first-order condition can be re-written as

$$p_I^* \frac{1}{2}\left[\frac{1}{m^*} h(x_3) - h(x_4)\right] \Delta_1^n - c = 0, \tag{25}$$

where x_3 and x_4 are defined above but with m^* replaced by m_I^{**}. Equation (25) implicitly defines the equilibrium share of authentic (high quality) antimalarials m_I^{**}. m_I^{**} is lower than m^*, defined in (14), for two reasons. First, as sophisticated consumers do not buy in period 2, the seller's marginal return schedule is shifted inward (since $\partial\rho_2^n/\partial m < \partial\rho_2^s/\partial m$) and as a consequence equilibrium quality falls. Second, as $p_I^* = p_{NGO} < 1$ and as half of the (naive) consumers now choose to buy their drugs from the NGO, the marginal return falls for all m, thus equilibrium quality falls.

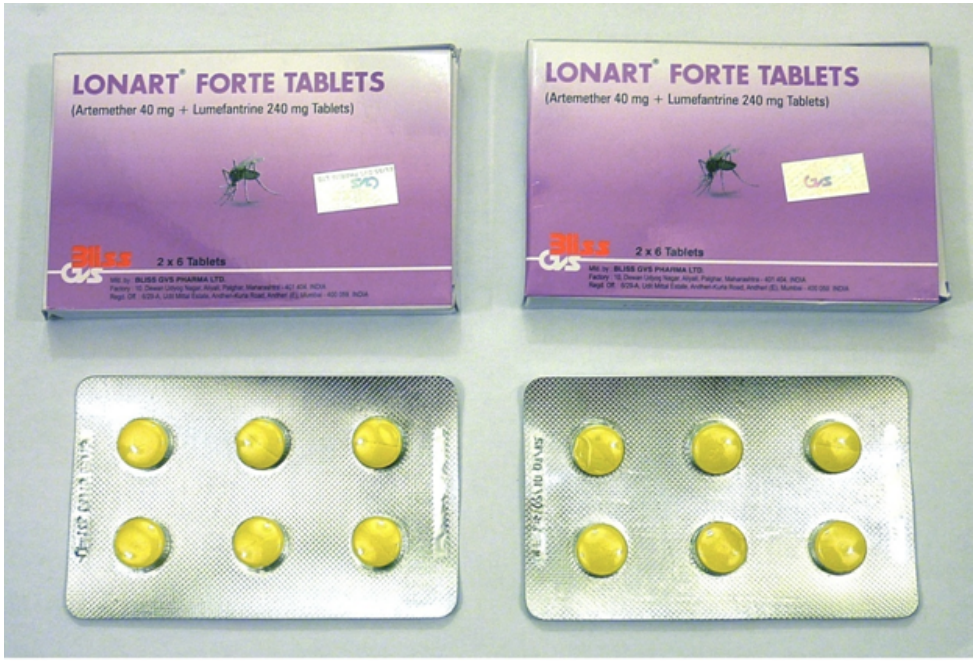

Figure 1. Examples of drug samples

Note: The figure shows two samples of antimalarial ACT from drug shops in Uganda. Sample A failed the quality test, indicating it is fake, and sample B is an authentic drug that passed the quality test.

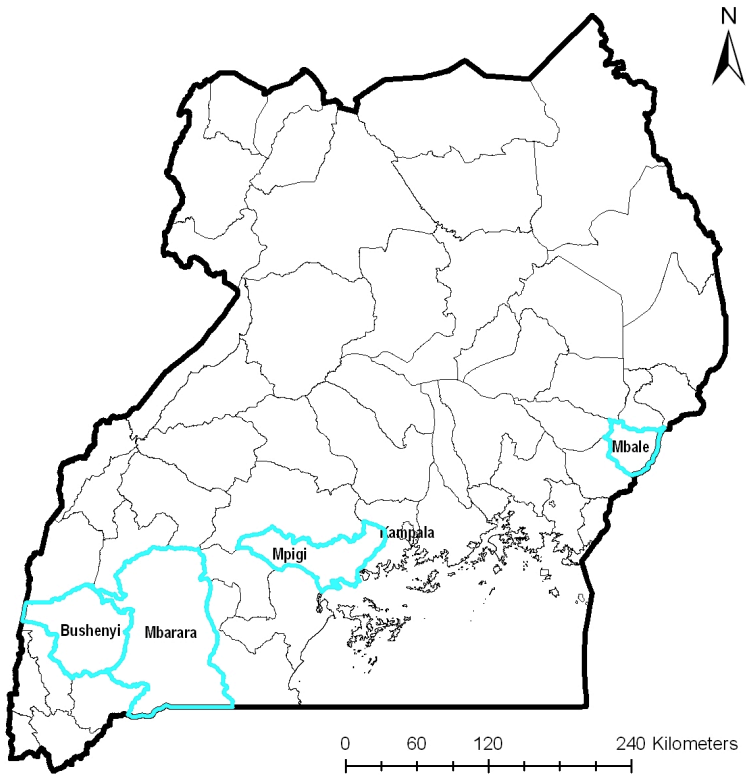

Figure 2. Sample districts in Uganda

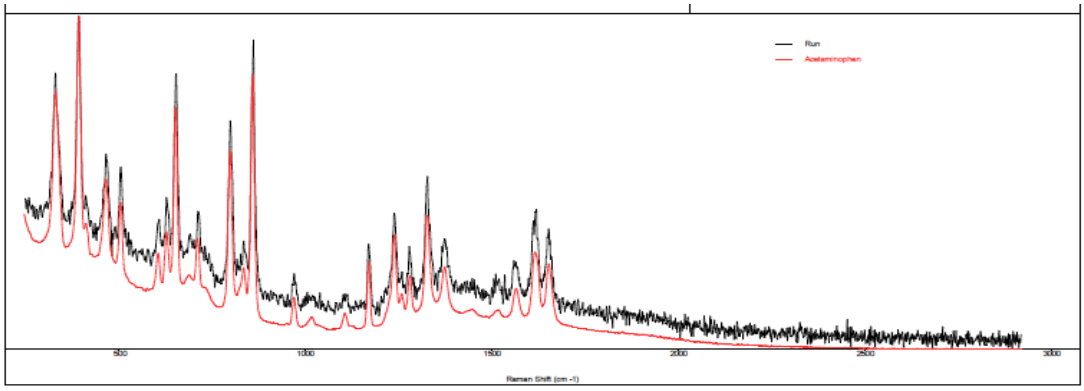

Figure 3. Raman spectroscopy drug authenticity test

Note: The graph shows an example of a drug quality test using Raman Spectroscopy. The black spectrum is the sample, while the red is the authentic reference. The method compares the Raman shifts ("spikes") of the test sample to the shifts of the authentic reference. If they are sufficiently similar, as given by a probabilistic algorithm, the sample passes the test and is considered authentic. The example above is a pass.

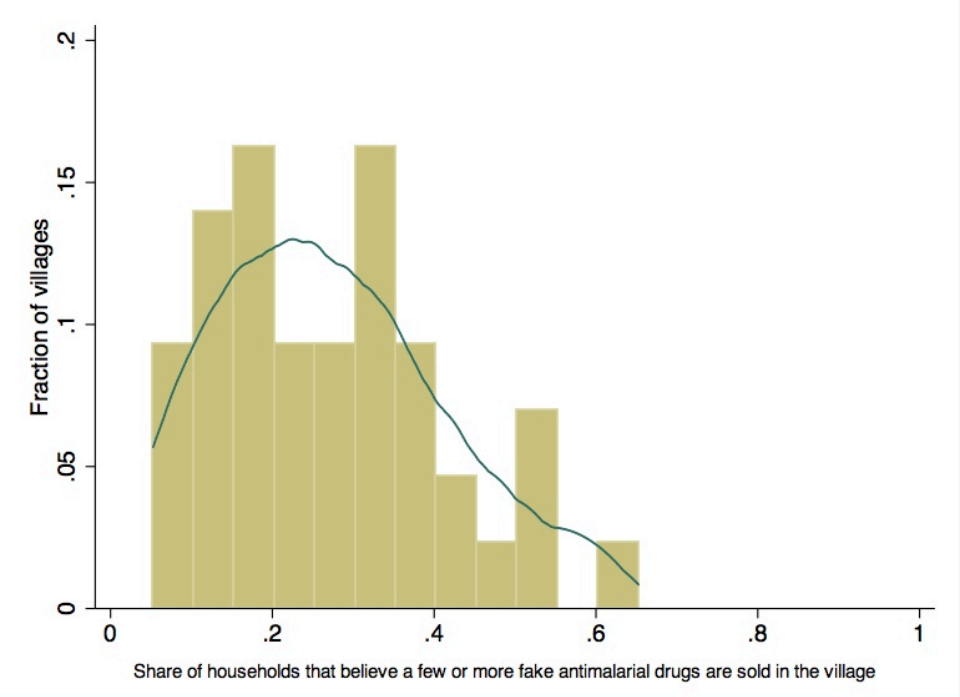

Figure 4. Beliefs about fake drugs across villages

Note: The x-axis variable is the fraction of the households in the village reporting that they believe the nearest drug shop in the village sells a few or more fake antimalarial drugs. The graph plots the histogram and kernel density of this variable across the villages in the baseline data. 27 percent of households believe the nearest drug shop sells fake drugs in the median village.

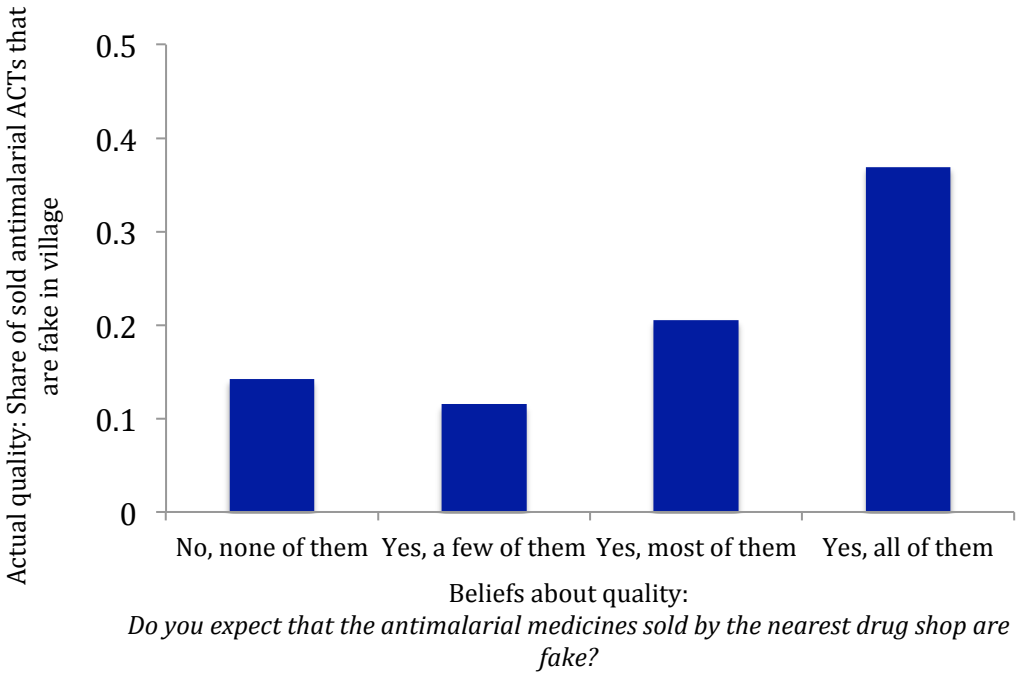

Figure 5. Beliefs of quality in drug shops and actual quality

Note: The figure shows how household beliefs about antimalarial drug quality correspond to actual quality in control villages. When households believe a large fraction of drugs is fake, the fraction of drugs that are fake is indeed larger.

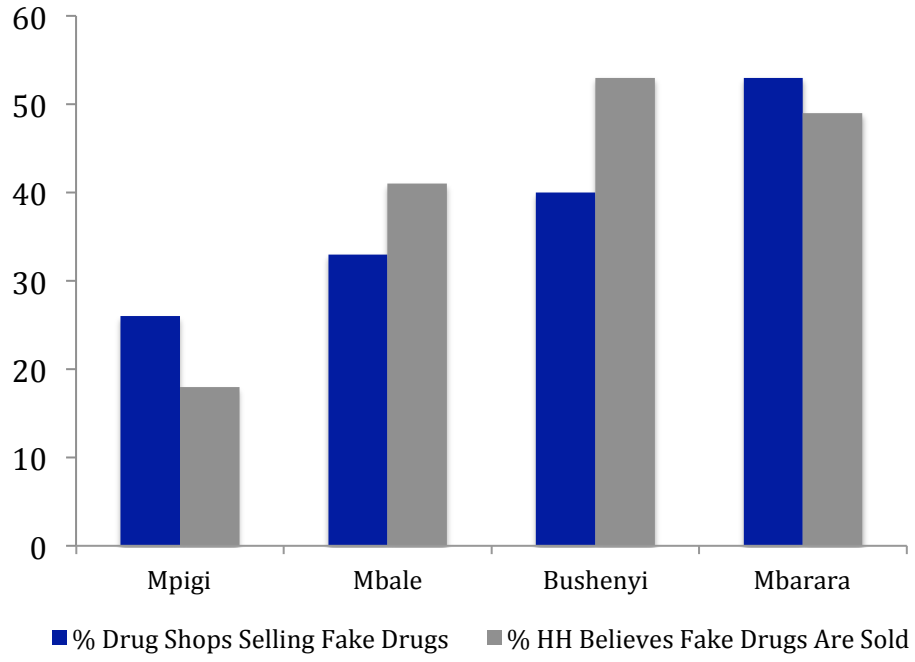

Figure 6. Quality and beliefs across districts

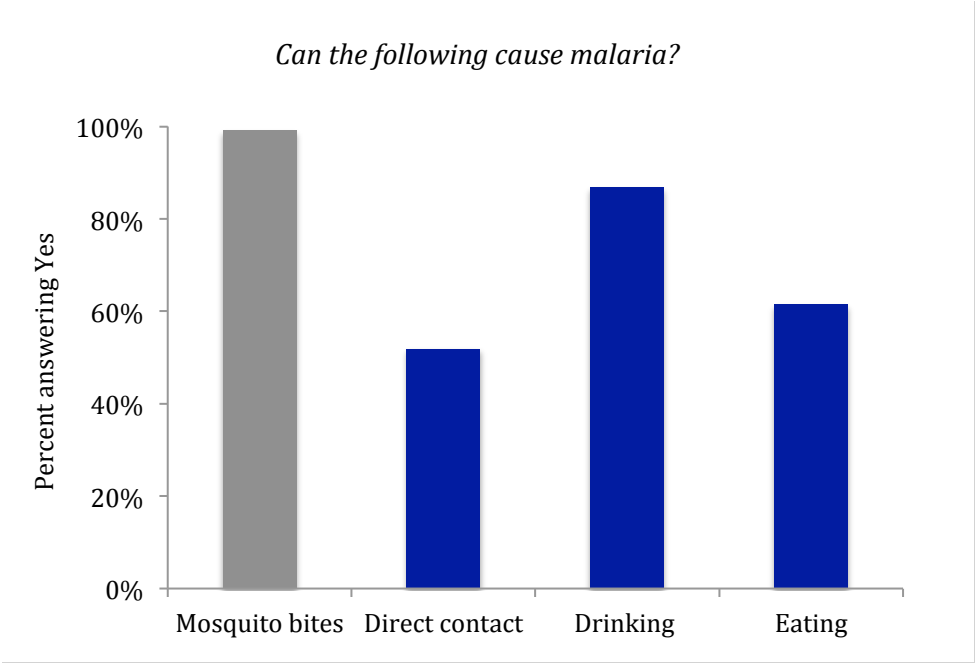

Figure 7. Misconceptions about malaria
Note: The graph shows summary statistics of households' beliefs about what causes malaria.

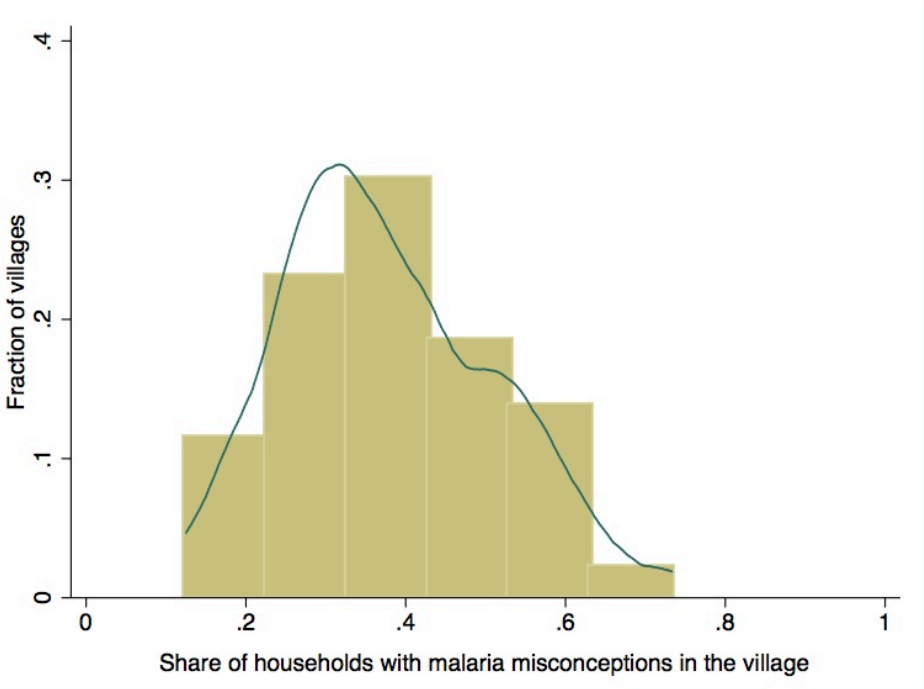

Figure 8. Distribution of misconceptions about malaria across villages
Note: The x-axis variable is the fraction of the households in the village that falsely believe that malaria can be caused by eating, drinking, and direct contact with someone that has malaria. The graph plots the histogram and kernel density of this variable across the villages in the baseline data. 35 percent of households in the median village have these misconceptions.

Table 1. Baseline Village Characteristics

	Treatment	Control	Diff	p-value
Village size (population)	201.0	198.8	2.2	0.96
	(192.9)	(202.4)		
Number of private drug outlets	1.36	1.65	-0.28	0.54
	(0.36)	(0.28)		
Share of villages with at least one private drug outlet	0.51	0.60	-0.09	0.36
	(0.51)	(0.49)		
Share of children under age 5 reported fallen sick with malaria in the last month	0.39	0.38	0.01	0.75
	(0.13)	(0.12)		
Share of households reporting to buy ACT:s to treat malaria (for children)	0.46	0.45	0.01	0.72
	(0.19)	(0.18)		
Share of HH heads with secondary education	0.34	0.29	0.05	0.11
	(0.16)	(0.17)		
Share of HH with radio	0.83	0.78	0.05	0.07*
	(0.11)	(0.14)		
Share of HH with television	0.13	0.10	0.03	0.29
	(0.02)	(0.02)		
Share of HH with electricity	0.15	0.13	0.02	0.59
	(0.03)	(0.02)		
Share of HH with sand or clay floors	0.46	0.50	-0.04	0.43
	(0.23)	(0.26)		
Share of HH with thatched roofs	0.04	0.05	-0.01	0.30
	(0.08)	(0.07)		
Share of HH that are Muslims	0.19	0.15	0.03	0.24
	(0.15)	(0.13)		

Note: The unit is survey cluster (village). Treatment is a door-to-door NGO distributor selling authentic ACT drugs in the village. Mean outcomes, with standard deviations in parentheses. There are 99 villages in the sample. P-values calculated using robust standard errors. The F-test does not reject the null hypothesis that all differences are zero (p-value=0.34).
** 5% , * 10% significance.

Table 2. Prevalence of Fake Antimalarial Drugs

	Drug shops selling fake drugs	Share of tested drugs that are fake	
	(1)	(2)	(3)
		All shops	*Conditional*
	36.8%	19.4%	51.5%
	(N=57)	(N=346)	(N=130)
By district			
Bushenyi	40.0%	30.0%	75.0%
Mbale	33.3%	11.1%	33.3%
Mbarara	53.3%	25.6%	47.9%
Mpigi	26.1%	14.1%	50.0%
By local competition			
Monopoly	30.8%	15.9%	46.4%
Competition	38.6%	20.5%	52.9%

A fake drug means that the drug (an ACT pill) failed the Raman Spectroscopy test. The sample consists of control villages. In column 1 the number of observations refers to the number of drug shops/pharmacies, and in columns 2-3 it refers to the number of tested pills. Column 2 reports the unconditional mean in the sample and column 3 reports the mean conditional on the shops selling fake drugs. Competition implies that there is more than one drug shop selling ACTs in the village.

Table 3. Signals of Quality: Price and Observable Characteristics

	Price		Observable Characteristics	
Dependent Variable:	Log(Price, Ush)		Share of inspectors of packages believing the sample contains fake drugs	
	(1)	(2)	(3)	(4)
Fake drugs sold, dummy	0.004		0.134	
	(0.056)		(0.126)	
Fake drugs sold, share		-0.085		0.084
		(0.069)		(0.118)
Constant	9.043***	9.061***	0.249***	0.282***
	(0.021)	(0.013)	(0.047)	(0.022)
Observations	57	57	57	57
R-squared	0.880	0.884	0.612	0.578
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
Village FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	9.0	9.0	0.298	0.298

Fake drugs sold means that the purchased ACT sample failed the Raman Spectroscopy authenticity test. The sample consists of drugs from shops in the 27 control villages. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 4. Expectations of Quality and Demand

	Treatment of children reported sick in malaria					
Dependent Variable:	Purchased drugs from drug shop, dummy		Treated with ACT, dummy		Number of ACT pills acquired	
	(1)	(2)	(3)	(4)	(5)	(6)
Believes drug shop sells fake drugs, dummy	-0.072**	-0.070**	-0.021	-0.017	-0.703**	-0.712*
	(0.034)	(0.034)	(0.051)	(0.052)	(0.343)	(0.395)
Radio ownership, dummy		0.020		0.095*		-0.115
		(0.054)		(0.048)		(0.517)
Television ownership, dummy		0.071		-0.039		0.788
		(0.062)		(0.058)		(0.474)
Electricity, dummy		0.035		-0.015		0.345
		(0.072)		(0.067)		(0.501)
Number of children in HH		-0.021		-0.002		0.314
		(0.018)		(0.027)		(0.363)
Muslim HH, dummy		-0.026		-0.027		-0.398
		(0.055)		(0.052)		(0.480)
Secondary education, dummy		0.036		0.041		0.471
		(0.042)		(0.052)		(0.454)
Tertiary education, dummy		0.055		0.144*		0.127
		(0.075)		(0.080)		(0.849)
Observations	949	949	949	949	320	320
R-squared	0.171	0.183	0.146	0.155	0.203	0.240
Unit of Analysis	Child	Child	Child	Child	Child	Child
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.68	0.68	0.37	0.37	6.66	6.66

The sample consists of children under age 5 reported sick with malaria in the last month. The respondent is the female head of the household. Beliefs about drug quality was measured by the question: "Do you expect that the antimalarial medicines sold by the nearest drug shop are fake?" The answer is given according to the likert scale: "No, none of them", "Yes, a few of them", "Yes, most of them", and "Yes, all of them". The dummy variable is equal to zero if the answer is "No, none of them", and one otherwise. The dependent variable in columns 1 and 2 is equal to one if the source was a private drug shop/pharmacy, and zero otherwise; in columns 3 and 4 it is equal to one if the treatment drug is ACT, and zero if it is some other antimalarial drug; and in columns 5 and 6 it is the number of ACT pills acquired conditional on the treatment drug being an ACT. Baseline data from treatment and control villages. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 5. Misconceptions about Malaria and Drug Quality

	Panel A: Expectations of quality in drug shop			Panel B: Actual quality in drug shop			
Dependent Variable:	Believes drug shop sells fake drugs, dummy			Drug shop sells fake drugs, dummy		Share of drugs that are fake	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Naive household, dummy	-0.061**	-0.063**	-0.077**				
	(0.030)	(0.029)	(0.030)				
Naive households, share of village				0.811**	1.226**	0.426***	0.590**
				(0.320)	(0.489)	(0.146)	(0.229)
Radio ownership		-0.060	-0.022		0.987		0.266
		(0.036)	(0.040)		(0.781)		(0.368)
Television ownership		-0.023	-0.016		0.478		-0.323
		(0.047)	(0.043)		(1.555)		(0.684)
Electricity		0.054	0.042		-0.360		0.261
		(0.043)	(0.037)		(1.213)		(0.550)
Number of u5 children in HH		-0.023*	-0.011		-0.404		-0.301*
		(0.013)	(0.013)		(0.310)		(0.153)
Muslim HH		-0.020	-0.015		0.866		0.127
		(0.030)	(0.032)		(1.066)		(0.431)
Secondary education		-0.055**	-0.050*		0.341		0.483
		(0.027)	(0.028)		(0.667)		(0.348)
Tertiary education		-0.086*	-0.077*		-0.887		-0.802
		(0.043)	(0.043)		(2.504)		(1.072)
Log(Number of households in village)					-0.080		-0.081
					(0.128)		(0.067)
Number of drug shops in village					0.003		0.007
					(0.046)		(0.020)
Observations	1435	1435	1435	57	57	57	57
R-squared	0.004	0.015	0.106	0.064	0.135	0.047	0.143
Unit of Analysis	HH	HH	HH	Drug shop	Drug shop	Drug shop	Drug shop
Village FE	No	No	Yes	No	No	No	No
Dep. Var. Mean	0.27	0.27	0.27	0.37	0.37	0.19	0.19

Panel A: Household data from all villages at baseline. *Naïve household* is a dummy equal to one if the female head falsely believes malaria can be caused by eating, drinking, and direct contact with someone who has malaria. The control variables and expectations of quality use the same definitions as in table 4. Panel B: Drug shop level data from control villages. The dependent variables measure fake drugs, defined as having failed the Raman Spectroscopy authencity test. The control variables are the village means from the baseline data. Robust standard errors in parentheses, clustered at the village level in all regressions. *** 1% , ** 5% , * 10% significance.

Table 6. Treatment Effect: Quality in Drug Shops

Dependent Variable:	Drug shop sells fake drugs, dummy		Share of sold drugs that are fake	
	(1)	(2)	(3)	(4)
NGO sells drugs	-0.197**	-0.212**	-0.108*	-0.126**
	(0.094)	(0.103)	(0.056)	(0.051)
Radio ownership		0.973		0.346
		(0.870)		(0.438)
Television ownership		0.220		-0.316
		(0.931)		(0.461)
Electricity		0.032		0.133
		(0.722)		(0.382)
Number of u5 children per HH		0.037		-0.027
		(0.300)		(0.141)
Muslim HH		-0.109		-0.347
		(0.593)		(0.272)
Secondary education		-0.249		0.304
		(0.753)		(0.419)
Tertiary education		-0.137		-0.077
		(1.720)		(0.927)
Log(Number of households in village)		-0.013		0.000
		(0.100)		(0.057)
Number of drug shops in village		-0.026		-0.027
		(0.040)		(0.023)
Observations	93	93	93	93
R-squared	0.074	0.103	0.085	0.134
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
Dep. Var. Mean in Control Villages	0.37	0.37	0.19	0.19

NGO sells drugs is a dummy variable equal to one if there is a door-to-door NGO distributor selling authentic ACT drugs in the village, and zero otherwise. The dependent variables measure fake ACT drugs, where fake means the sample failed the Raman Spectroscopy authencity test. All regressions include district fixed effects. Robust standard errors in parentheses, clustered at the village level. There are 47 villages in the sample. *** 1% , ** 5% , * 10% significance.

Table 7. Treatment Effect: Price in Drug Shops

Dependent Variable:	Log(Price, Ush)		Price, '000 Ush	
	(1)	(2)	(3)	(4)
NGO sells drugs	-0.146**	-0.165***	-1.449**	-1.557***
	(0.058)	(0.048)	(0.564)	(0.386)
Radio ownership		0.923**		6.090*
		(0.381)		(3.123)
Television ownership		-1.088***		-7.793***
		(0.272)		(2.347)
Electricity		0.792**		5.144**
		(0.299)		(2.540)
Number of children per HH		-0.119		-1.374
		(0.108)		(0.894)
Muslim HH		0.239		2.009
		(0.216)		(2.116)
Secondary education		0.095		0.846
		(0.291)		(2.118)
Tertiary education		0.973		13.689**
		(0.736)		(6.071)
Log(Number of households in village)		-0.096**		-0.892***
		(0.040)		(0.326)
Number of drug shops in village		-0.031*		-0.204
		(0.016)		(0.138)
Observations	93	93	93	93
R-squared	0.531	0.671	0.515	0.658
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
Dep. Var. Mean in Control Villages	9.0	9.0	8.91	8.91

NGO sells drugs is a dummy variable equal to one if there is a door-to-door NGO distributor selling authentic ACT drugs in the village, and zero otherwise. The control variables are village means from the baseline data. All regressions include district fixed effects. Robust standard errors in parenthesis, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 8. Treatment Effect: Quantity and Expectations of Quality in Drug Shops

	Treatment of children reported sick in malaria						Expectations of quality in drug shop	
Dependent variable:	Purchased drugs from private drug shop, dummy		Treated with ACT, dummy		Number of ACT pills acquired		Believes drug shop sells fake drugs, dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO sells drugs	-0.090	-0.080	-0.002	0.007	2.67***	2.60**	-0.076**	-0.080**
	(0.090)	(0.088)	(0.078)	(0.081)	(0.76)	(0.95)	(0.031)	(0.029)
Observations	275	275	275	275	174	174	584	584
R-squared	0.168	0.172	0.013	0.049	0.13	0.16	0.013	0.019
Unit of Analysis	Child	Child	Child	Child	Child	Child	HH	HH
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Dep. Var. Mean in control villages	0.48	0.48	0.66	0.66	6.73	6.73	0.34	0.34

The independent variable is a dummy equal to one if there is a door-to-door NGO distributor selling authentic ACT drugs in the village, and zero otherwise. In columns 1-6, the sample consists of children under age 5 reported sick with malaria in the last month. In columns 7-8, the sample consists of households. The respondent is the female head of household in all regressions. The dependent variables: In (1)-(2) a dummy equal to one if the child was treated with an ACT, and zero if it was some other antimalarial drug; in (3)-(4) a dummy equal to one if the treatment was acquired from a drug shop/pharmacy, and zero otherwise; in (5)-(6) it is the number of ACT pills that were acquired for treatment; in (7)-(8) it is a dummy equal to one if the household believes that the nearest drug shop sells fake antimalarial drugs, and zero otherwise. The control variables are dummies for radio ownership, TV ownership, electricity, and Muslim household. No data on education was collected in the post survey. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 9. Heterogeneous Effects on Drug Quality: Misconceptions about Malaria

Dependent Variable:	Drug shop sells fake drugs, dummy		Share of drugs that are fake	
	(1)	(2)	(3)	(4)
Naïve households * NGO sells drugs	1.79**	2.26**	1.46*	1.86**
	(0.81)	(0.94)	(0.85)	(0.72)
NGO sells drugs	-0.78**	-0.93***	-0.60**	-0.73***
	(0.31)	(0.34)	(0.29)	(0.25)
Naive households	0.78*	1.12***	0.43**	0.70***
	(0.40)	(0.41)	(0.19)	(0.20)
Observations	93	93	93	93
R-squared	0.14	0.19	0.16	0.24
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
Controls	No	Yes	No	Yes
Dep. Var. Mean in Control Villages	0.37	0.37	0.19	0.19

NGO sells drugs is a dummy variable equal to one if there is a door-to-door NGO distributor selling authentic ACT drugs in the village, and zero otherwise. *Naïve households* is the share of households in the village at baseline that falsely believe malaria can be caused by eating, drinking, and direct contact with someone who has malaria. The control variables are the same as in table 6. Robust standard errors in parenthesis, clustered at the village level. *** 1% , ** 5% , * 10% significance.