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

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May 2012

Abstract

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 quality.

JEL CODES: D83, I15, O12

KEYWORDS: Malaria, counterfeit medicine, asymmetric information, ACT, field experiment

*We are grateful for comments and suggestions by Philippe Aghion, Tessa Bold, Raquel Fernandez, Asim Khwaja, Michael Kremer, Nancy Qian, and Richard Zeckhauser, as well as seminar participants at Harvard/MIT, IIES, LSE, and NYU for their valuable comments. We would also like to thank Annalise Blum, Deanna Ford, Sarah McCune, and Charles Ntale for excellent research assistance and management, and CIFF, Living Goods and BRAC for their collaboration. All mistakes are our own. Financial support from the Swedish Research Council (421-2009-2209); the Program for Development Research, SIDA; J-PAL; William F. Milton Fund; and Harvard Center for Population and Development Studies is gratefully acknowledged.

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1 Introduction

3.3 billion people are at risk of malaria worldwide 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 efficacious 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 antimalaria 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 ninety five villages in four districts in Uganda.[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. We further find that many consumers are aware of fake drugs in the market, as 27% of the household respondents report that they believe drug shops in their village sell fake antimalarial drugs, but misconceptions about how malaria is transmitted are common.

To understand the determinants of drug quality and to guide the empirical work, we first present a simple model of the market under local monopoly. The model features characteristics of the antimalarial medicine market that we believe are important in order to understand how drug quality is determined. Specifically, consumers (patients) face uncertainty as to whether they have malaria or some other febrile disease (e.g., viral or bacterial). Drug quality is unobservable before purchase, but consumers may partially infer quality by observing health outcomes after taking the drugs.

[1] In a meta-analysis of published and unpublished work reporting chemical analyses of antimalarial drugs in south-east 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 ACT:s can have both direct short and long run adverse effect on health outcomes by failing to reduce the parasites 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 development of malaria 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 (products resulting from poor manufacturing by the authorized manufacturer resulting in inadequate content). We use the term fake drugs for drugs that fail chemical analyses using Raman spectroscopy (see section 4).

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

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. This, in turn, hampers learning and leads consumers to overestimate antimalarial drug quality. 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.

When then present a set of simple facts and correlations consistent with the assumptions and predictions of the model. First, prices do not signal quality across outlets within the same local market, a result that stands in contrast with the key predictions of existing models of experience goods (Wolinsky, 1982; Milgrom and Roberts, 1986), or in models with adaptive learning and reputation (Shapiro, 1982). Second, we find evidence suggesting that households are able to infer quality, although not perfectly: households that suspect that a higher fraction of drugs are fake 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. Third, beliefs about drug quality matter for demand, even conditional on actual quality. Fourth, 'naive' consumers with misconceptions about malaria are less likely to believe that fake drugs are sold. 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 low quality 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? 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 the question, we conduct a randomized experiment across the 95 local markets in our sample. Specifically, and in the spirit of Akerlof's (1970) discussion of counteracting market of 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 with 11 percentage points, corresponding to a decrease in fake drugs by 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.

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) improve. This forces the incumbent drug shop to sell fewer fake drugs in order not to 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 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*.[4] Thus, while we focus on a particular – albeit an important – market our findings are of more general interest. In fact, a growing body of mostly anecdotal evidence from developing countries suggests that many other markets with products sharing key characteristics of the antimalarial drugs, for example the market for agricultural inputs, are also characterized by counterfeit and substandard products. Studying such markets is important since poor product quality for inputs not only can directly affect productivity but also people's willingness to experiment and adopt new technologies. And 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).

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 comparing health outcomes. Second, empirically, we measure quality directly and relate this to prices and beliefs about quality. Third, we provide experimental evidence from an intervention aimed at changing the market equilibrium. The paper is also related to the literature on (unobserved) provider quality in the health sector in developing countries.[5] It also relates to a growing

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

[5]See for instance Das et al. (2008) and the reference given therein.

literature on how markets function when regulations aimed at correcting externalities are circumvented by corruption. Unlike Olken and Barron (2009) and Bertrand et al. (2007), however, our focus is not on the agent in charge of implementing the regulation, in this case to safeguard public health, but on the agents the regulation is aimed to control.

The paper is structured in the following way. Section 2 describes important features common to antimalarial markets. Section 3 presents the model and discusses its assumptions and implications. Section 4 describes the experimental design and the data. Summary statistics and correlations are presented in section 5 and the experimental results are discussed in section 6. 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 the 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 underlying 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 underlying cause. Third, evidence from medical anthropology shows that misconceptions about what is causing 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 red blood cells causing symptoms that typically include fever and headache. In severe cases, it can progress to coma or death. In Africa alone there were 174 million cases of malaria and an estimated 596 000 to over 1 million deaths in 2010, most of them children under five (WHO, 2011; Murray

et al., 2012). Uganda has one of the world's highest malaria incidence, 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 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 malaria.

By failing to reduce the parasites load or delaying treatment with high quality medicines, poor quality ACT:s can have direct adverse effect on health outcomes, including increased morbidity and mortality. It can also have long run adverse effects. A 2006 systematic review of 18 studies concluded that untreated or inadequately treated *plasmodium falciparum* malaria in 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).[6] 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 development of malaria resistance. A key priority to prevent ACT resistance, therefore, 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.[7] As many infectious diseases mimic malaria both in initial symptoms and in signs of severe illness, however, 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.

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. And even when blood slide microscopy, considered to be the gold standard for malaria diagnosis, is available, it is often not used and has low accuracy (Amexo et al., 2004).[8] A

[6] 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.

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

[8] Maintaining a high quality microscopy service is a major challenge for primary health clinics as blood slide

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 malaria positive blood slides were in fact negative (Zurovac et al., 2006). Compliance to test results, both by individuals and health practitioners, is also weak.[9] Moreover, rapid diagnostic tests (RDT:s), which are 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 exposed to unnecessary side-effects of drugs, and the true cause may not be treated or treated with delay, 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 for poorer households, treatment of malaria, as well as diagnosis, 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 various private providers, with informal and unregulated private outlets being the most common provider.

Studies on health seeking behavior document similar patterns. Nuwaha (2002), for example, 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, and recurrent stock-outs, Rutebemberwa et al. (2009) find that two thirds of febrile children in a predominantly rural area in Eastern region of Uganda were treated at home with drugs from informal drug shops and private clinics.[10]

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

microscopy depends on well-maintained equipment, supply of good-quality reagents, and experienced and trained lab technicians.

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

[10] For example, Bold et al (2011) find in a representative sample of 170 primary health clinics in Tanzania that 22% of the clinics did not have any ACT:s in stock. 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.

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 mangoes infected with mosquito eggs, are important transmission channels.[11]

If consumers attribute illnesses caused by bacterial, viral or parasitic infections to malaria, and as many of these diseases often are self-limited, implying 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

Artemisinin derivatives is the most effective group of drugs against *Plasmodium falciparum* malaria. Its key substance, artemisinin, is a compound derived from Chinese wormwood trees. Artemisinin is significantly more expensive to produce then older, synthetic forms of malaria medicine. Multiple brands of ACTs exist and the retail price for a dose in Sub-Saharan Africa is around 4-8 USD.

A number of 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 were falsified (Narray et al., 2012). There is also evidence that the problem appears to be growing over time (Newton et al., 2011).

[11] 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 associate convulsions, a symptom of severe malaria, as caused by mosquito bites. Instead, many believed that it was caused by evil spirits and thus choose traditional remedies for treatment.

Counterfeit and substandard quality is, however, not a specific problem for antimalarial drugs. 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, rising in certain markets in parts of Africa and Asia to over 50%.

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. For sub-standard drugs, costs could be cut 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 are have been listed as the main sources countries of poor quality ACTs (Lybecker, 2004). Anecdotal evidence also suggests that repackaging of non-ACT:s 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

Quality of an ACT drugs is difficult to distinguish based on visual characteristics as evident from figure 1 which depicts two packs and blister packages from two samples of ACT:s purchased and tested in our study: one fake and one authentic. More systematic evidence is presented in Dondorp et al. (2004). They compare counterfeit ACT:s 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 are very similar to the 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). Empirically, however, there is scant evidence on the relationship between quality and price in the pharmaceutical market in 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 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, show the market in rural areas is usually characterized by low competition, with 51% of local markets (villages) served by a local monopoly and 23% by local duopolies. The private providers are also typically small and often unlicensed.

3 A Model of a Local Drug Market

In this section we present a simple model of a local drug market. The model takes its starting point in the evidence presented in section 2. Thus, we assume that consumers (patients) do not know whether they have malaria or some other febrile disease. They also cannot observe whether the antimalarial drug they buy is authentic or not. In the model, consumers can be of two types: sophisticated consumers that have the correct biomedical model for malaria transmission and use Bayesian updating of drug quality based on health outcomes, and naive consumers who update but have the wrong model linking malaria and health outcomes.

The model is solved under two different scenarios. First we consider the case where there is a local monopoly in the market (the control group outcome). We then extend the model and introduce a competitor – a NGO – which sells high quality antimalarials at subsidized prices (the treatment group outcome). In both scenarios, our focus is on the incumbent profit maximizing seller's choice of quality and price.

3.1 Setup

There are two active players in the model: drug store sellers and consumers. Consumers are clustered at two points (a and b), located at a distance d from each other, with $d \in (\frac{1}{2}, 1)$, and each with a mass of consumers given by unity. The drug store is located at point a.

There are two periods. In each period t consumers fall sick in what they believe might be malaria. Consumers, however, cannot tell whether they have malaria or some other febrile illness. Let the actual share of consumers that falls sick in malaria in period t be denoted by q_t, while a share w falls sick in some other, self-limiting, disease. The malaria shock q_t is drawn from a uniform distribution on the interval $\left[\underline{q}, \bar{q}\right]$, with $\bar{q} + w \leq 1$.

A consumer recovers quickly if she suffers from malaria and if she is treated with an authentic (high quality) antimalarial. In addition, consumers with other self-limiting illnesses recover, independent of the quality of treatment, with probability 1. Let m_t denote the share of authentic (high quality) antimalarials sold by the drug store in period t. Then a share s_t of the consumers, given in (1), that buy antimalarial drugs recovers quickly.

$$s_t = q_t m_t + w \tag{1}$$

Consumers can be of two types: sophisticated consumers and naive consumers, of which a share $g \leq 1$ are assumed to be sophisticated. Both types observe treatment status and s_t. The share of authentic antimalarials sold by the drug store, m, and the malaria shock, q, are unobservable. Sophisticated consumers, however, know the distribution of q. They also observe w, or can estimate it by comparing health outcomes between those that treat their fever with antimalarials and those that do not. Thus, each sophisticated consumer knows the correct biomedical model for malaria transmission, given in (1), although they do not observe q and m. Naive consumers make systematic errors regarding malaria. Specifically they do not realize, or do not take into account, that a share w of consumers falls sick in some other, self-limiting, disease. Thus, they assume that q is drawn from a uniform distribution on the interval $\left[\underline{q}, \bar{q} + w\right]$ and use the incorrect model (2) for the share of consumers that recover quickly conditional on treatment.

$$s_t = q_t m_t \tag{2}$$

Since naive consumers' beliefs are inconsistent with observed outcomes, we assume they do not make comparisons in health status across space or conditional on treatment status.[12]

[12] They are inconsistent with observed outcomes as a share w of the untreated consumers still recover quickly, implying that all consumers cannot have malaria.

Drug shop sets the share of authentic (high quality) antimalarials to sell m, with $m \in [0,1]$. The cost of selling a share of m high quality drugs is $c(m) = cm$, with $c > 0$.

There are three types of drug shop owners: honest H, opportunistic O, and dishonest D. Nature draws the type at the start of period 1. With probability π_H the seller is honest, with probability π_O the seller is opportunistic, and with probability π_D the seller is dishonest. An honest seller sets $m = 1$, a dishonest seller sets $m = 0$, while an opportunistic seller sets $m \in [0,1]$. Sellers know their own preferences (that is, their types). Consumers know the proportions π_H, π_O, and π_D.

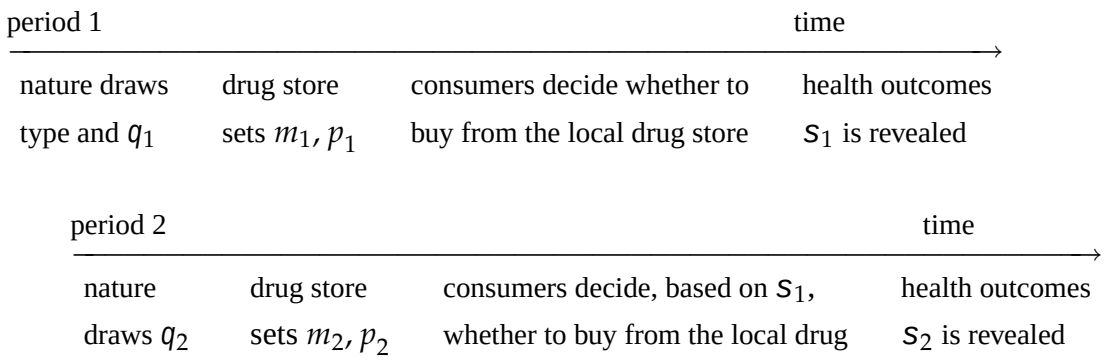
Denote the consumers' beliefs or estimate of the seller's quality choice conditional on type as $\tilde{m}_a^k$, with $k = \{H, O, D\}$ denoting types. As the honest and dishonest types choose m mechanically, and this is known by consumers, we let $\tilde{m}_a^H = 1$ and $\tilde{m}_a^D = 0$.

Consumers vary in their willingness to buy potentially substandard antimalarials, or vary in what they consider to be sufficient quality. Specifically, assume consumers are willing to buy a drug from the drug shop if the expected quality is above some threshold value j, where j is distributed uniformly among the consumers, $j \sim U[0,1]$. Thus, if we normalize the consumers' valuation of treatment to 1, we can write consumer i:s preferences as

$$D(r \geq j_i) - p, \tag{3}$$

where r is the expected quality of the drug, $D(.)$ is an indicator function taking the value 1 if $r \geq j_i$ and 0 otherwise, and p is the price of the drug.[13] The timing of the game is illustrated in figure 1.

Figure 1: Timing of the Game.



[13] The fact the households are willing to pay a maximum price of 1 for treatment could be rationalized by assuming that consumers either are credit constrained or that consumers can buy (high quality) drugs from a public provider at a price (including transport costs) $p = 1$.

3.1.1 Solution: The Monopoly Case

The solution concept is perfect Bayesian equilibrium (PBE), where strategies of the players are optimal given beliefs and beliefs are obtained from strategies and observed actions/outcomes using Bayes' rule.

To solve the problem note first that no consumer would purchase a drug from the drug shop if the price is above the marginal value of treatment 1. Thus, if $d > 1/2$ the profit maximizing price is $p = 1$ and the monopoly seller only caters to consumers at point a.[14]

Given that authentic drugs are costly, in the second (last period) the opportunistic seller will choose $m_2 = 0$

(6) $$r_2^n = \frac{m_H(s-\underline{q})}{m_H(s-\underline{q}) + m_O\left(\frac{s}{\tilde{m}_a^O} - \underline{q}\right)}$$

As evident from (3), a consumer buys the antimalarial drug from the drug shop if the price is no higher than 1 and the expected quality r_2 is above a threshold value j. Thus, the expected share of consumers that will buy from the seller, or expected quantity demand in period 2, $\bar{q}_2$, is equal to the average expected quality

$$\bar{q}_2 = \bar{r} \equiv g r_2^s + (1-g) r_2^n.$$

In period 1, the expected quality of the medicine as perceived by the consumers, and thus demand, is $r_1 = m_H + m_O \tilde{m}_a^O$.

Consider now an opportunistic seller's maximization problem. The seller will choose m so as to maximize expected profits, given in (7), taking consumers' beliefs and strategies as given,

(7) $$\max_{m_1} r_1 + gE\left[r_2^s(m_1)\right] + (1-g)E\left[r_2^n(m_1)\right] - cm_1,$$

Without loss of generality, we let $m_H = m_O = m_D = 1/3$. The first-order condition, which equates the marginal gain, taking the form of higher expected quality and thus higher demand, with the marginal cost c, can be simplified to

(8) $$E\left[g\frac{gq\left[\frac{1}{\tilde{m}_a^O} - 1\right]\underline{q}}{\left[qm - \underline{q} + \frac{qm}{\tilde{m}_a^O} - \underline{q}\right]^2} + \frac{(1-g)q\left[\frac{1}{\tilde{m}_a^O} - 1\right]\underline{q}}{\left[qm + w - \underline{q} + \frac{qm+w}{\tilde{m}_a^O} - \underline{q}\right]^2}\right] - c = 0\,.$$

In equilibrium, the seller's quality choice is consistent with the consumers' expectations or beliefs, so $\tilde{m}_a = m_1 = m^*$. The equilibrium share of authentic (high quality) antimalarials is thus implicitly defined by equation (9),

(9) $$E\left[\frac{gq\left[\frac{1}{m^*} - 1\right]\underline{q}}{[(1-m^*)q - 2\underline{q}]^2} + \frac{(1-g)q\left[\frac{1}{m^*} - 1\right]\underline{q}}{\left[(1-m^*)q + w\left(1 + \frac{1}{m^*}\right) - 2\underline{q}\right]^2}\right] - c = 0$$

Total differentiating (9) yields

$$\frac{\P m^*}{\P g} > 0 \tag{10}$$

That is, the higher the share of sophisticated consumers, the higher the share of authentic drugs in equilibrium. Intuitively, naive consumers incorrectly perceive that consumers that actually did not suffer from malaria but still recovered quickly did so because they suffered from malaria and were treated with an authentic antimalarial drug. Thus, for a given m, the seller's expected demand from naive consumers is higher than that from sophisticated ones. As r_2^s and r_2^n; i.e. sophisticated and naive consumers perceived likelihood that high quality pills will be sold in period 2, are increasing concave functions of m, however, the seller's expected marginal return is lower for naive as compared to sophisticated consumers. As a consequence, the expected weighted marginal return to higher quality, the terms in the bracket in (10), falls in the share of naive consumers.

3.1.2 Entry by an Honest NGO

Consider now an extended model with an additional seller (a NGO) that sells high quality antimalarials. Assume the two sellers are located at point a (the "incumbent") and point b (the "NGO"). The NGO brands itself as a high quality seller that sells ACTs at a subsidized prize. 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 below, that it sets a price $p_b = p_{NGO}$ and $m_{NGO} = 1$.

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 seller's type. Specifically, relative health outcomes is

$$\frac{s_a}{s_b} = \frac{m_a q + (1-q)w}{m_{NGO} q + (1-q)w}. \tag{11}$$

If $s_a/s_b < 1$, sophisticated consumers can conclude that $m_a < m_{NGO}$ and since honest types by assumption chooses $m = 1$, that the incumbent seller cannot be an honest type.[16]

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

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

Proposition 1: *If condition A1 holds and if the share of naive consumers is sufficiently low, there exist an equilibrium in which the seller at point a, consistent with the consumers' beliefs, chooses* $\hat{m}^* = 1$ *in period 1 and sets prices* $p^* = p_{NGO} + d < 1$.

(A1) $$p^* \frac{1}{2} > c,$$

Corollary 1: *The seller at point a will set a lower price than in the monopoly case provided that*

(A2) $$p_{NGO} < 1 - d$$

Proposition 2: *For a sufficiently high share of naive consumers, the equilibrium drug quality is* $\check{m}^* < 1$, *where* $\check{m}^*$ *is implicitly defined by condition A3.*

(A3) $$(1-g)p^* E\left[\frac{(1-g)q\left[\frac{1}{\check{m}^*}-1\right]\underline{q}}{\left[(1-\check{m}^*)q + w\left(1+\frac{1}{\check{m}^*}\right) - 2\underline{q}\right]^2}\right] - c = 0\,.$$

Corollary 2*: With a sufficiently large share of naive consumers, the equilibrium drug quality,* $\check{m}^*$, *is lower than in the monopoly case.*

Proof: As $g \to 1$, the seller's only relevant options are to set $m_1 = 1$ or to set $m_2 = 0$, as all $m > 0$ (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 seller at a sets $m_a = m_{NGO} = 1$. Further, let $\tilde{m}_a^O = \tilde{m}_{NGO}^O = 1$. The NGO is assumed to set the price p_{NGO}. Given the distance d between sellers, the highest price the seller at point a can set without losing its customers is then

(12) $$p^* = p_{NGO} + d$$

Seller a:s expected profits, $E[p]$, is

(13) $$E\left[p \,|\, m = 1, \tilde{m}_a^O = 1\right] = p^* \frac{2}{3} + p^* \frac{1}{2} - c$$

as $r_2^s = r_2^n = \frac{1}{2}$ and $r_1 = \frac{2}{3}$ when $m = \tilde{m}_a^O = 1$. Deviating and choosing $m = 0$ yields expected

profits

$$E\left[p|m=0,\tilde{m}_a^O=1\right]=p^*\frac{2}{3} \tag{14}$$

Comparing expected profits, equations (13) and (14), yields condition A1.

The seller at point a sets the price $p=1$ in the monopoly case and $p^*=p_{NGO}+d$ when facing competition. Thus, if A2 holds, price competition will increase with the entry of the NGO and the equilibrium price will fall.

Consider the alternative scenario when $g\to 0$. Then the seller only caters to naive consumers. Given beliefs $\tilde{m}_a^O$, the seller's maximization program is

$$\max_{m_1}\ (1-g)p^*\left[r_1+E\left[r_2^n\right]\right]-cm,$$

and the new equilibrium condition, implicitly defining the equilibrium m, denoted by $\check{m}^*$, is given by A3.

The equilibrium drug quality $\check{m}^*$ is lower than in the monopoly case, defined in (10), for two reasons. First, as sophisticated consumers do not buy in period 2, the seller's marginal return schedule is shifted inward and as a consequence equilibrium quality falls. Second, if $p_{NGO}<1-d$, the marginal return falls for all m, thus equilibrium quality falls. ■

With the NGO on the market, sophisticated consumers can distinguish the quality choice from the health shock. As the NGO by assumption sets $m_{NGO}=1$, the only way for the incumbent seller to ensure that sophisticated consumers will buy in the future is to mimic the NGO and also set $m=1$. Such as strategy is optimal provided that the share of naive consumers is not too large; that is, provided that the reputational concerns are sufficiently important.

3.2 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 5 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 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 (a NGO) selling high quality and subsidized antimalarial medicines.

Below we discuss the main assumptions and predictions of the model.

1. Price and quality. In the model, and by assumption, price and quality (the share of authentic drugs) are determined by two separate mechanisms. The degree of spatial competition determines the price of the antimalarial drugs. As the model assumes that quality cannot be directly distinguished based on observable characteristics, the quality choice is driven by sellers' incentive to build up or maintain reputation. Thus, price differences do not reflect or signal quality differences: $Corr(p^*, m^*) = 0$.

2. Expectations of quality and actual quality. In the model, consumers infer quality based on observable health outcomes in the village. There are two types of consumers in the model: sophisticated (unbiased) and naive (biased) consumers. Thus, although the average expectation can be biased, since there is some learning, expected quality will be increasing in actual quality in equilibrium: $\P\bar{r}/\P m^* > 0$. This in intuitive as the higher the share of authentic drugs sold by the drug shop, the higher the share of patients recovering quickly from treatment. As a consequence, consumers revise up their beliefs that the seller is honest.

3. Expectations of quality and quantity demanded. Consumers value authentic drugs, and are willing to purchase drugs if the expected share of authentic drugs is sufficiently high. The prediction is therefore that quantity demanded is increasing in expected quality, $\P\bar{q}_2/\P\bar{r} > 0$.

4. 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 w of consumers get fever due to other, self-limiting, viral or bacterial infections. Therefore, conditional on actual quality m^*, naive consumers expect fewer fake drugs and overestimate quality,

$$\textbf{4a)} \text{ Conditional on } m^*,\ r_2^n > r_2.$$

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,

$$\textbf{4b)}\ \frac{dm^*}{dg} > 0.$$

5. Treatment effect: Quality. When the NGO enters 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,

$$\hat{m}^* > m^*$$

6. Treatment effect: Price. The degree of spatial competition determines the price of the anti-malarial drugs. When the NGO enters and sell authentic the incumbent outlet will *lower its price* provided that the distance between the two sellers and/or NGO:s price are low enough.

7. 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, the demand curve shifts outward. Second, a lower price leads to movement along the demand curve.

8. Heterogeneous treatment effects: Misconceptions about malaria. In expectations the effect of NGO entry on incumbent drug quality is *decreasing* in the fraction of naive consumers, $1 - g$. 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. Thus the incumbent seller's incentive to increase quality in order to maintain a good reputation when faced with competition falls in the share of naive consumers.

4 Experimental Design and Data

4.1 Experimental Design

The experiment involved 95 rural villages (Local councils) in four districts (Bushenji, Mbale, Mbarara, and Mpigi) in Uganda with high and endemic *P. falciparum* malaria prevalence (figure 2).

The experiment is part of a long-run impact evaluation of a market-based community health care program in Uganda. The community health care evaluation is following a large set of villages (or clusters), organized into 10 branches, of which seven branches are managed by BRAC and three 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.

[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.

For the drug quality study, three BRAC branches and the largest of the three Living Goods' branches were selected. Altogether 95 villages were thus includes, of which 47 [48] were treatment [control] sites.

4.2 Data

We combine a cross-sectional dataset on drug quality with two rounds of household survey data in four districts (see figure 2). First, we conducted a census of drug outlets and households in the 95 project villages. We then collected baseline household survey data in all villages in the first half of 2010, followed by a drug quality survey in 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: purchase and testing of ACT medicine. On the former, we trained a set of enumerators with knowledge of the local area and language on how to use a script when approaching the outlet. According to the script, the covert shopper was buying medicine for his/her sick uncle. The covert shopper 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 from light in a dry and cool place. We purchased ACT drugs from all private outlets that sold ACT in the 95 villages. In total, 559 pills from 94 outlets in 43 villages were purchased.

Chemical analyses of medicines like ACT:s can be performed using several techniques.[18] Our method of quality testing is Raman spectroscopy, using a TruScan handheld scanner. By exposing the sample (pill) to laser and measuring the reflecting Raman spectra, the molecular composition of each sample tablet is tested against an authentic reference database. The method is able to detect with high precision whether the pill is authentic or not (pass/fail).[19] Figure 3 shows an example of the Raman spectrum of a tested sample. As scanning a tablet takes about a minute, an important advantage of Raman spectroscopy compared to laboratory methods is speed. Another important advantage is that compared to laboratory testing that 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,

[18] As discussed in Nayyar et al. (2012), Raman spectroscopy is one of several techniques to test for medicine quality.

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

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).[20]

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 surveyor visually inspected each sample and made an assessment of whether they believed the drugs were fake or not. To set the prior beliefs approximately consistent with the data, the inspectors were informed that thirty percent of the samples were fake. Samples were individually presented in a sequence (without any additional information), and the inspectors' assessment were reported after each sample.

To measure households' beliefs about antimalarial quality in the drug shops, we asked each 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 direct contact with someone who has malaria, from mosquito bites, from drinking contaminated water, and from eating "infected mangos". Since mosquitoes are the biological vectors through which malaria is transmitted, three of the four statements are thus false. Figure 4 shows the summary statistics of the beliefs about malaria among respondent in the baseline data. 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. 99 percent of the respondents correctly answer that malaria can be caused by mosquito bites. Thus, a naive consumer is essentially one that falsely believes that ingestion and direct contact (which can cause fever due to bacterial, viral or non-Falciparum parasitic infections) can cause malaria. In the sample, 35 percent of the respondents are labeled as naive.

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

[20]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.

4.3 Intervention

Once the treatment status was assigned, the collaborating NGOs (Living Goods and BRAC) recruited and trained a woman from the 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.[21] The CHP keeps the difference.

The CHP is expected to sell the ACT:s to household in the village she is assigned. 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 to 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.[22]

4.4 Empirical Strategy

We combine the household data with the drug quality data. To establish facts, we first run simple correlations. To assess the impact of the intervention, we use OLS to estimate the following specification

$$y_{ovd} = \beta NGO_v + \lambda_d + \gamma X_{vd} + \varepsilon_{ovd}, \tag{15}$$

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 woman/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

[21] 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.

[22] 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.

include district fixed effects λ_d.

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

$$fake_{ovd} = \beta NGO_v + \gamma naive_v + \eta(NGO * naive)_v + \lambda_d + \delta X_{vd} + \#_{ovd}, \quad (16)$$

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 4 and 8 imply $\gamma > 0$ and $\eta < 0$.

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

4.5 Pre-intervention Statistics

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 ACT:s 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 in 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.

5 Results: Facts and Correlations

We first present simple correlations and summary statistics, using data from the baseline survey. We also use data on drug quality from control villages. Motivated by the model, we focus on five results: the extent of poor quality drugs (counterfeit and substandard); the correlation between price and quality; whether beliefs about quality are correlated with actual quality; whether beliefs

about quality is correlated with the choice of where to seek treatment; and if drug quality is negatively correlated with the share of households holding false beliefs about malaria transmission and treatment.

Prevalence of fake ACT:s

How common are counterfeit and substandard ACT:s? Table 2 provides summary statistics of the prevalence of fake drugs. 36.8% of the outlets sell fake ACT:s. The prevalence is highest in the western, and most rural, districts (Bushenyi, 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.[23]

Prediction 1: Price and Quality

In our model, and in Akerlof's (1970) classical lemons model, we assume that quality cannot be observed before purchase, and high and low quality products have the same price within a given market. However, other theories suggest that price and quality should be correlated in equilibrium, and that price may signal quality to consumers (Shapiro, 1982; Wolinsky, 1982; Milgrom and Roberts, 1986). Using the 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 effect, 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

consumers may be able to use observable characteristics of the package to assess quality. Columns 3 and 4 use the data from the visual inspections of the samples. There is little evidence that observable characteristics reveal quality. While the coefficients are positive, the point estimates are small and not statistically significant at conventional levels. This indicates that it is difficult to infer quality solely based on observable characteristics of the products.

Prediction 2. Expectations of quality and actual quality

In the model, households may infer quality based on observable health outcomes (although not necessarily in an unbiased manner). Are households aware of the high prevalence of fake drugs? Figure 5 shows the distribution of beliefs about drug quality across villages. A high fraction of consumers believe fake drugs are sold. In the median village, 27 percent of the female head of households report that they expect the nearest drug shop to sell some fake antimalarial drugs. There is also substantial variation in beliefs across villages.

Figure 6 shows how households' beliefs about drug quality correspond to actual quality in drugs shops in the control villages.[26] As evident, when households suspect a high prevalence of fake drugs in the nearest drug shop, the prevalence of fake drugs is indeed higher. Figure 7 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 some learning takes place. However, beliefs are far from perfect. For example, among households that believe that the nearest drug shop does not sell fake drugs, a fair fraction (16 percent) of the drugs sold in their village are not authentic (figure 6). 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). This suggests that some learning takes place, but that the learning is noisy.

Prediction 3. 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.[27] To hold quality in the market constant, we exploit variation across households within the same local 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

[26] We exclude treatment villages since beliefs and quality may depend on the intervention.

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

including household controls, which suggests that the relationship simply does not reflect income effects or heterogeneity in costs of going to the public health centers. Columns 3-6 investigate

likelihood that an outlet sells fake drugs (column 5), and a 9.0 percentage points increase in the share of fake drugs sold by drug shops (column 7).

Interpretation

To summarize, the results in tables 3-5 are correlations. Interpreted within our theoretical framework, however, they provide suggestive evidence on 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 quality, possibly by observing health outcomes conditional on treatment as in the model. However, consumers' ability to learn appear 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, the beliefs consumers hold about drug quality appear to affect demand, as higher expectations are associated with higher quantity purchased, 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 a 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 5-8, and present causal evidence on the impact of the intervention on market outcomes.

6 Results: Treatment Effects

Can superior products drive out inferior ones?[29] In this section we estimate the effects of entry by the NGO selling authentic ACT drugs on market outcomes. We are interested in testing four hypotheses. First, we test whether the intervention improved drug quality among incumbent drug shops. Second we assess whether price and quantity was affected. Finally, we investigate whether imperfect consumer learning due to misconceptions about malaria is an important determinant of market quality.

Prediction 5. Treatment Effects on Quality

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

Table 6 shows that the intervention increased quality in incumbent drug shops. Having a NGO outlet in the local market decreased the likelihood that an incumbent drug shop sells fake ACT:s 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. Consistent with prediction 5, 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.

Prediction 6. 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 7. 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 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 invention therefore substantially increased the size of the market for ACTs, consistent with prediction 7.[30]

Do consumers respond by increasing demand because quality is higher, or are the quantity effects simply due 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.

[30]The number of pills acquired on is still below the full dose for the average child.

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 is approximately -2. A priori, this seems implausible large. Experimental data from rural Kenya by Cohen et al. (2011) also indicates that the price elasticity is much smaller. They estimate that the price elasticity of ACT demand is -0.084 for treatment of individuals of all ages. For young children their results indicate that the demand curve is actually slightly upward sloping.

Second, consumer expectations of drug quality in incumbent drug shops change. 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 8. 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 coefficient in columns 1-4 indicate that the effects on drug quality is 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.[31] Together with table 6, these results indicate that misconception about malaria influence antimalarial drug quality, as opportunistic drug shops find it more profitable to sell poor quality antimalarials when consumers have difficulties in correctly inferring 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 (a monopoly) 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

[31] 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.

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 ACT:s 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 we assess a combined effect we cannot rule out that the lower price had an impact on our finding on quality. For example, it is possible that the lower price increased the take-up of ACT:s 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 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 data from the control group shows there is no significant relationship between measures of competition (like the number of outlets in the market) and the likelihood that fake drugs are sold, suggesting that competition alone is not enough to drive out fake medicines. 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 quality of ACT:s with observational data on market structure and survey data on consumer behavior and beliefs across almost 100 rural villages in Uganda, we show that poor quality ACT:s 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 market of 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 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 reasons for the growing problem of counterfeit and substandard ACT:s in Africa is 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 of the regulatory framework and improved enforcement of existing regulations might be the first-best, however, 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 NGO:s 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, NGO:s may provide a partial solution to the public health problem of poor quality drugs. Second, and more suggestive, health education addressing poor knowledge and misconceptions about malaria transmission may not only improve the match between illness and treatment, but also, though households' ability to infer quality, raise drug quality on the market.

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 (RDT:s) 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 losing reputation. That is, RDTs may not only reduce overtreatment of malaria but may also improve drug quality. Moreover, 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. 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 not only can 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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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.

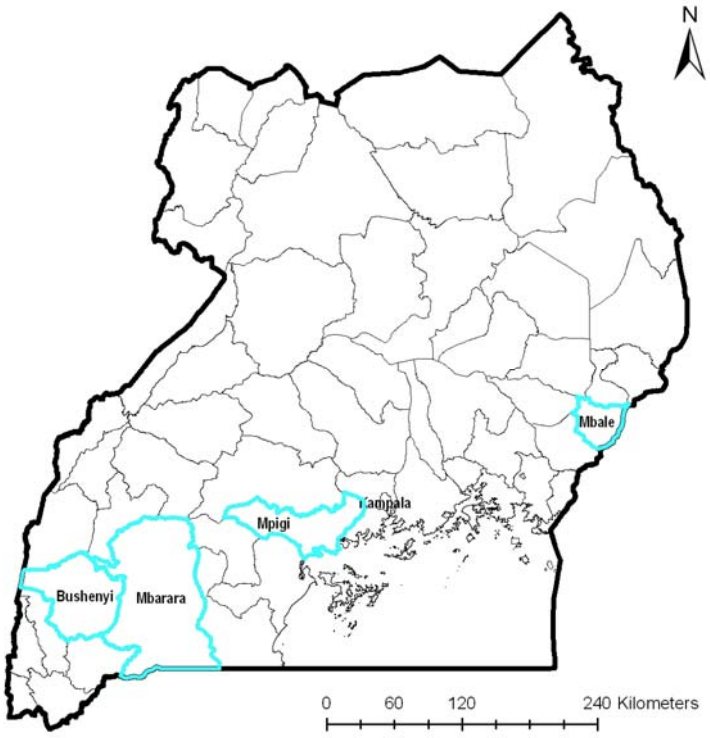

Figure 2. Sample districts in Uganda

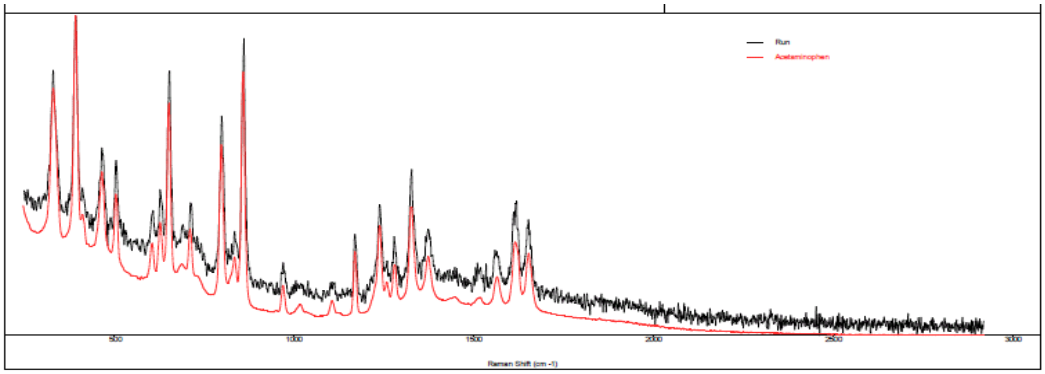

Figure 3. Raman Spectroscopy Drug Authenticity Test

Note: The graph shows an example of a drug quality test using Raman spectroscopy. The black spectrum is the sample and the red spectrum 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.

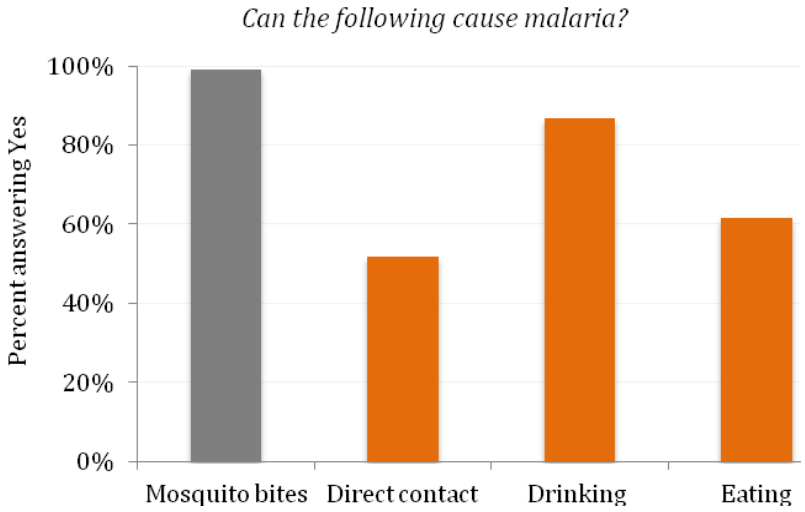

Figure 4. Misconceptions about Malaria.

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

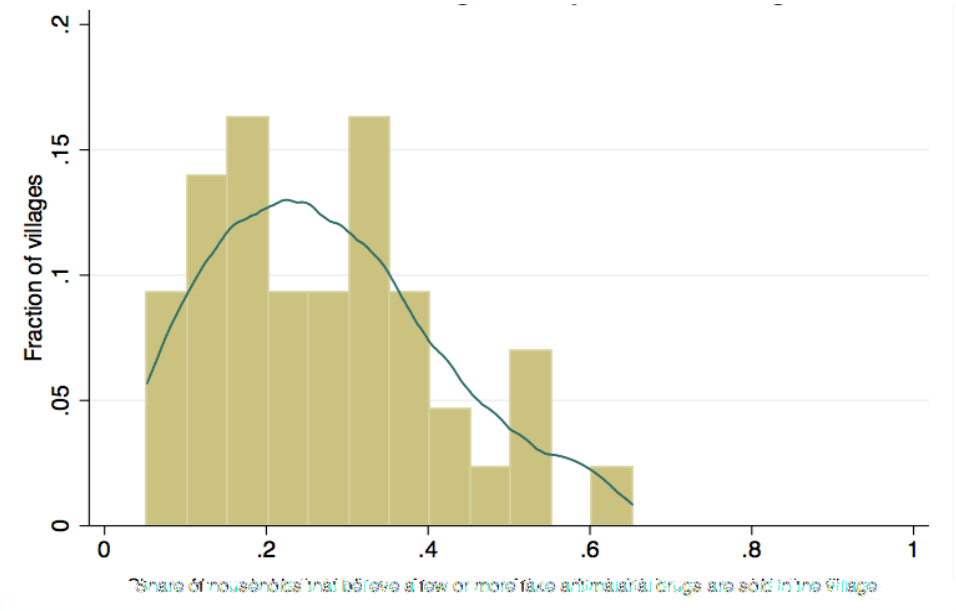

Figure 5. Distribution of Beliefs about Drug Quality Across Villages
Note: The x-axis variable is the fraction of the households in the village that report that they believe the nearest drug shop in the village sells fake antimalarial drugs. The graph plots the histogram and kernel density of the variable across the villages in the baseline data. 27 percent of households believe the nearest drug shops sells fake drugs in the median village.

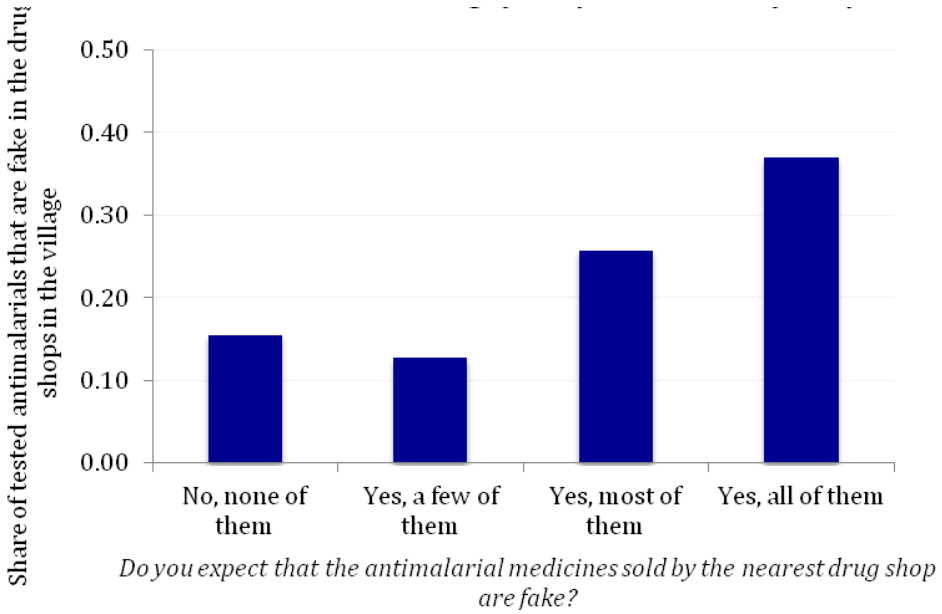

Figure 6. Beliefs of Quality in Drug Shops and Actual Quality
Note: The figure shows how households' beliefs about antimalarial drug quality correspond to actual quality in control villages.

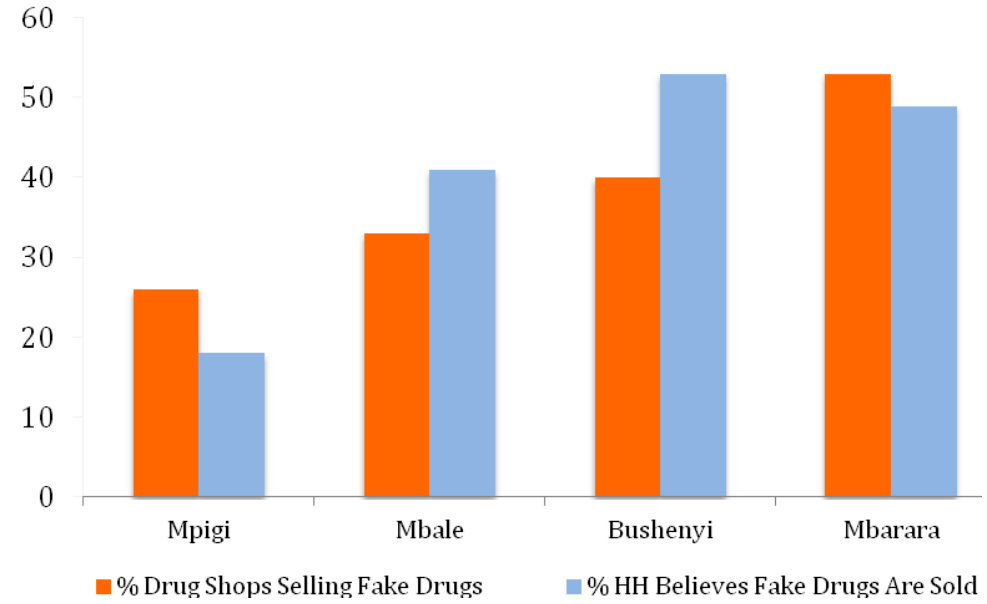

Figure 7. Actual Quality and Beliefs about Quality Across Districts
Note: The figure shows how households' beliefs about antimalarial drug quality correspond to actual quality in control villages across districts.

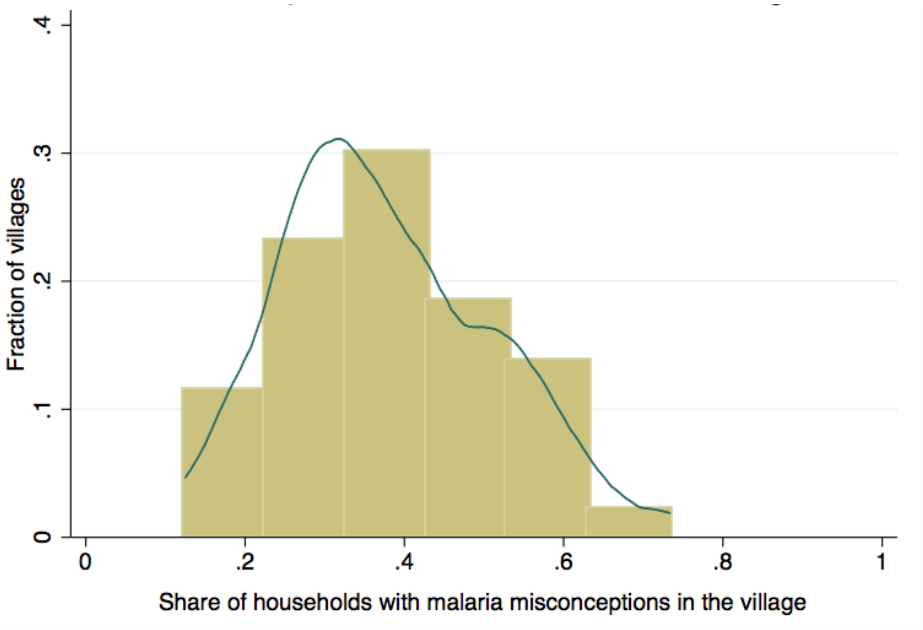

Figure 8. Distribution of Misconceptions about Malaria Across Villages
Note: The x-axis variable is the fraction of the households in the village that falsely believe that malaria can be caused by eating, drinking, and direct contact with someone that has malaria. The graph plots the histogram and kernel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

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 village. Treatment is the NGO entrant selling authentic ACT drugs in the village. Mean outcomes, with standard deviations in parentheses. P-values calculated using robust standard errors. 95 villages of which 47 are in the treatment group. 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 ACT Drugs

	Drug shops selling fake drugs	Share of drugs that are fake	
	(1)	(2)	(3)
		All shops	*Conditional*
All districts	36.8%	19.4%	51.5%
	(N=57)	(N=346)	(N=130)
Districts			
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%

A fake drug means that the sample (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 of all 57 drug shops. Column 3 reports the mean conditional on the shops selling fake drugs.

Table 3. Signals of Quality: Price and Observable Characteristics

	Price		Characteristics	
Dependent Variable:	Log(Price, Ush)		Share of inspectors believing the sample contains fake drugs	
	(1)	(2)	(3)	(4)
Fake drugs sold, dummy	0.008		0.136	
	(0.051)		(0.120)	
Fake drugs sold, share		-0.059		0.061
		(0.069)		(0.121)
Constant	9.042***	9.056***	0.248***	0.287***
	(0.029)	(0.024)	(0.039)	(0.038)
Observations	57	57	57	57
R-squared	0.863	0.865	0.597	0.787
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 the purchased ACT sample failed the Raman spectroscopy authencity test. The sample consists of drugs from 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 in 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. The dependent varibale in columns 3 and 4 is equal to one if the treatment drug is ACT, and zero otherwise. The dependent variable in columns 5 and 6 is the number of ACT pills acquired conditional on the treatment with ACT. Baseline data from the 43 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**
				(0.303)	(0.476)	(0.145)	(0.223)
Radio ownership		-0.060	-0.022		0.987		0.266
		(0.036)	(0.040)		(0.800)		(0.375)
Television ownership		-0.023	-0.016		0.478		-0.323
		(0.047)	(0.043)		(1.575)		(0.692)
Electricity		0.054	0.042		-0.360		0.261
		(0.043)	(0.037)		(1.204)		(0.546)
Number of u5 children in HH		-0.023*	-0.011		-0.404		-0.301*
		(0.013)	(0.013)		(0.335)		(0.162)
Muslim HH		-0.020	-0.015		0.866		0.127
		(0.030)	(0.032)		(1.179)		(0.483)
Secondary education		-0.055**	-0.050*		0.341		0.483
		(0.027)	(0.028)		(0.694)		(0.357)
Tertiary education		-0.086*	-0.077*		-0.887		-0.802
		(0.043)	(0.043)		(2.574)		(1.102)
Log(Number of households in village)					-0.080		-0.081
					(0.128)		(0.067)
Number of drug shops in village					0.003		0.007
					(0.047)		(0.021)
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 level baseline data from all villages. Naïve household is a dummy equal to one if the female head falsely believes malaria can be caused by contaminated water, eating "infected mangos", and from 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**
	(0.099)	(0.104)	(0.059)	(0.053)
Radio ownership		0.973		0.346
		(0.873)		(0.442)
Television ownership		0.220		-0.316
		(0.977)		(0.485)
Electricity		0.032		0.133
		(0.759)		(0.406)
Number of u5 children per HH		0.037		-0.027
		(0.271)		(0.141)
Muslim HH		-0.109		-0.347
		(0.639)		(0.288)
Secondary education		-0.249		0.304
		(0.757)		(0.420)
Tertiary education		-0.137		-0.077
		(1.823)		(0.956)
Log(Number of households in village)		-0.013		0.000
		(0.105)		(0.059)
Number of drug shops in village		-0.026		-0.027
		(0.041)		(0.024)
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 the NGO sells 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 43 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***
	(0.060)	(0.050)	(0.576)	(0.405)
Radio ownership		0.923**		6.090*
		(0.385)		(3.174)
Television ownership		-1.088***		-7.793***
		(0.280)		(2.451)
Electricity		0.792**		5.144*
		(0.318)		(2.756)
Number of children per HH		-0.119		-1.374
		(0.113)		(0.959)
Muslim HH		0.239		2.009
		(0.233)		(2.294)
Secondary education		0.095		0.846
		(0.293)		(2.138)
Tertiary education		0.973		13.689**
		(0.766)		(6.436)
Log(Number of households in village)		-0.096**		-0.892***
		(0.040)		(0.330)
Number of drug shops in village		-0.031*		-0.204
		(0.016)		(0.140)
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 the NGO sells 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

NGO sells drugs is a dummy variable equal to one if the NGO sells authentic ACT drugs in the village, and zero otherwise. In columns 1-6, the sample consists of children under age 5 reported sick in 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 drugs were purchased from the private drugs shops, and zero otherwise; in (3)-(4) a dummy equal to one if the child was treated with an ACT, and zero otherwise; in (5)-(6) the number of ACT pills that was acquired for treatment; in (7)-(8) 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**
	(0.79)	(0.95)	(0.85)	(0.73)
NGO sells drugs	-0.78**	-0.93***	-0.60**	-0.73***
	(0.31)	(0.34)	(0.30)	(0.25)
Naive households	0.78*	1.12***	0.43**	0.70***
	(0.40)	(0.40)	(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 the NGO sells authentic ACT drugs in the village, and zero otherwise. *Naïve households* is the share of households in the village at baseline that falsely believe that malaria can be caused by contaminated water, eating "infected mangos", and from 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.