The Market for (Fake) Antimalarial Medicine: Evidence from Uganda *

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Abstract

We study the determinants of antimalarial drug quality in developing countries using data from the retail market in Uganda. We find that common biomedical misconceptions among consumers are associated with overly optimistic beliefs about quality, and lower quality sold by retailers. We use a field experiment and find that entry by an NGO selling authentic drugs significantly reduced fake drugs among incumbents, with weaker effects in markets where consumer misconceptions were relatively pervasive. The results are consistent with a simple experience good model where biomedical misconceptions decrease consumers' ability to infer quality, which retailers exploit by selling lower quality medicines.

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1 Introduction

A large share of the estimated 0.6-1.2 million deaths that occur each year due to malaria could be avoided if households had access to medicines that are known be effective (WHO, 2011a; Murray et al., 2012). There is growing evidence, however, that the market for antimalarial medicines is plagued by counterfeit and substandard products (Arrow et al., 2004), with recent estimates suggesting that a third of drugs sold are fake.[1] A wide variety of regulatory policies have recently been put forward to address the problem of fake drugs.[2] Information about the determinants of quality and how the market for medicines works – about which little is currently known – is essential to the evaluation of many of these new initiatives.

Antimalarial medicine is an experience good. That is, consumers observe neither the quality of the medicine sold nor the utility it will yield before purchase. In markets for such products, sellers typically face a moral hazard problem: they have short-term incentives to cut costs by lowering quality, but could earn higher profits by commiting to high quality (Mailath and Samuelson, 2001). Since reputation can be viewed as a commitment device that allows sellers to solve the moral hazard problem, and because the incentives to establish and maintain a reputation depend on consumer learning, the process and ability by which consumers gather and process information is crucial to the understanding of how the market functions (Shapiro, 1982).

In this paper we use data from Uganda to investigate the market for artemisinin-based combination therapy (ACT), the WHO first-line recommended treatment for malaria. We first present the data we collected to establish a set of facts. Using a covert shopper approach and testing for authenticity using Raman Spectroscopy, we show that the market is characterized by quality problems: 37 percent of the private drug shops, a majority of them local monopolies, sell fake ACT drugs.[3] Based on household survey data, we further show that biomedical misconceptions about malaria are common: a majority of households believe that malaria is transmitted in ways attributable only to non-malarial febrile diseases, such as direct contact with someone who has malaria. Drawing on insights from several strands of the literature, we then focus on three interrelated questions using non-experimental data: are consumers easily able to infer whether drugs are fake, or is this

[1] In a meta-analysis of published and unpublished work reporting chemical analyses of antimalarial drugs in Southeast Asia and sub-Saharan Africa, Nayyar et al. (2012) estimate that 32 percent of the tested samples were falsified, meaning the sample contained too little or no active pharmaceutical ingredients, or contained an unstated drug or substance. Estimates indicate that approximately 0.25 million deaths per year would be preventable if episodes treated with counterfeit and substandard antimalarial drugs were instead treated with genuine and non-substandard drugs (Harris et al., 2009). We use the term fake to indicate counterfeit and substandard drugs.

[2] In a recent Lancet editorial, for example, the authors call for the strengthening of drug regulatory authorities, as well as the enactment and enforcement of new laws to prohibit fake drugs.

[3] Raman Spectroscopy is a common method used to detect counterfeit and substandard drugs. We describe the method in section 5.3.

process prohibitively difficult and noisy?[4] Is learning about drug quality hampered by consumers' biomedical misconceptions about malaria? Do such misconceptions determine actual drug quality in the retail market? To answer these questions, we present a simple experience good model of how misconceptions lead consumers to deviate from Bayesian learning, and how the prevalence of such misconceptions in turn affects the incentive to sell fake antimalarials.[5]

We find that consumers are generally aware of the problem of fake drugs, but that the relationship between perceived and actual quality across markets is weak, indicating that inference of, or learning about, drug quality is noisy for many consumers. We find that consumers with biomedical misconceptions are less likely to believe that the nearest drug shop sells fake antimalarials. They are also more likely to be overly optimistic about quality by incorrectly predicting there are no fake drugs sold by village shops that, in fact, sell fake drugs. This is consistent with the hypothesis that misconceptions hamper consumers' ability to infer drug quality. We also find evidence that these misconceptions seem to matter for equilibrium quality, as the likelihood of drug shops selling fake drugs is significantly higher in villages where misconceptions are more widespread, controlling for various socio-economic consumer characteristics. The estimated association also suggests a quantitatively meaningful effect, as a one standard deviation increase in the share of consumers with misconceptions is associated with a 21 percentage point higher likelihood that an outlet sells fake drugs.

We then exploit experimental variation in competition in the market for antimalarial drugs to gain further insights into the determinants of quality. Using data from an ongoing randomized controlled field trial, we show how incumbent private outlets and consumers react to the entry of an NGO selling authentic ACT drugs below local market prices. In our simple model, the exogenous entry of a high quality outlet can improve households' ability to learn about quality by implicitly providing them with information on relative health outcomes from treatment with ACTs across outlets. In response, an incumbent outlet's short-run incentive to cut costs by lowering quality is weaker, and actual and perceived quality increase. We further hypothesize that since the learning environment is worse when consumers have biomedical misconceptions about malaria, the entry of a high quality seller will have less of an impact on the incumbent's quality decision when the market is dominated by this type of consumer. The experimental evidence is consistent with these

[4] Adhvaryu (2012), Dupas (2010), and Kremer and Miguel (2007) also analyze the process of learning about and adopting health technologies. Our focus, however, is on a largely overlooked factor, namely that the markets for these new technologies are often corrupted in countries with weak institutions.

[5] For a recent review of the research on nonstandard beliefs that deviate from Bayesian learning, see DellaVigna (2009). The interaction between consumers with various biases and profit-maximizing firms is a central theme in the boundedly rational industrial organization literature (e.g., Gabaix and Laibson, 2005), also surveyed in Ellison (2006). In our framework, misconceptions influence market equilibria in a similar fashion to Barberis et al. (1998). This implies that, for example, individuals interpret data incorrectly if their beliefs correspond to an erroneous model of the world.

hypotheses. After the NGO entered a village, the share of authentic ACTs sold by the incumbent drug shops increased by 11-13 percentage points, corresponding to a decrease in fake drugs of approximately 50 percent. Consistent with the reduction in fake ACT drugs and increased learning about quality, households are 11-13 percentage points less likely to believe that incumbent shops in the treatment villages sell fake antimalarials. Finally, we find that the estimated treatment effect on drug quality is significantly weaker in villages where misconceptions about malaria are more prevalent, which is consistent with the hypothesis that reputation forces to provide high quality goods are weaker when consumers face difficulties inferring quality.[6]

Antimalarial drugs form part of a wider set of products where quality is not directly observable at the time of purchase, and only partially observable when used. Thus, while we focus on a particular, albeit important, market, our findings also apply to markets beyond pharmaceutical products. Evidence and news reports suggest that product quality in markets for experience goods, such as fertilizers and seeds, gasoline, auto parts, electronics, baby food, and hygiene products (Mwakalebela, 2012; Tentena, 2012; Rajput, 2012; OECD, 2008), is notoriously low in developing countries due to counterfeiting. Studying markets for these products is important not only because trade may be sub-optimally low as a result of counterfeiting, but also because poor product quality for inputs can directly affect productivity, as well as people's willingness to experiment and adopt new technologies. Furthermore, even if quality differences are small for each input, they could result in large differences in aggregate output (Kremer, 1993). Moreover, while counterfeit medicines have traditionally been more of a concern in developing regions, where regulatory and enforcement systems for medicines are weak, counterfeiting has become more and more prevalent in developed countries as drug supply chains increasingly cross continents through online markets (Lancet, 2012). Across all products, international trade in counterfeit goods is estimated to be 250 billion USD, and when domestically produced and consumed goods are included, the magnitude of counterfeiting worldwide is estimated to be over 600 billion USD (OECD, 2008; BASCAP, 2011). The overall problem and potential welfare consequences are therefore non-trivial.

The paper is structured as follows. Section 2 describes important features common to antimalarial markets in sub-Saharan Africa. Section 3 presents a simple two-period model to highlight possible mechanisms. Section 4 describes the data and the empirical design. Section 5 presents the empirical findings. Section 6 concludes.

[6]We also find that the NGO entry decreased prices, consistent with the existence of significant mark-ups in the retail market, and that drug quantity demanded (measured as ACT treatment of children reported sick with malaria) increased. Our results therefore indicate that the NGO entry increased consumer surplus and decreased producer surplus among incumbent firms.

2 The Market for Antimalarial Drugs: Demand and Supply

2.1 Demand

Malaria is a mosquito-borne infectious disease. The disease causes symptoms that typically include fever and headache. *Plasmodium falciparum,* the most common type of malaria in sub-Saharan Africa, accounts for the majority of deaths. In Africa alone there were 174 million cases of malaria in 2010, and an estimated 596 000 to over 1 million deaths, mostly children under the age of five (WHO, 2011a; Murray et al., 2012). Uganda has one of the world's highest malaria incidences, with a rate of 478 cases per 1000 individuals per year (WHO, 2005).

Adequately and promptly treated, malaria is a curable disease, but severe malaria can develop from seemingly uncomplicated and untreated cases within hours. Treatment of malaria within 24 hours is important in order to reduce the likelihood of morbidity, severe damage, and death (Getahun et al., 2010). Artemisinin-based combination therapy (ACT) is currently recommended by the WHO as the first-line treatment of *Plasmodium falciparum* malaria. Multiple brands of ACTs exist, and the retail price for a dose in sub-Saharan Africa is typically around 3-8 USD. Compared to older, synthetic forms of malaria medicine, artemisinin is significantly more expensive to produce.

Poor quality ACTs can have a direct adverse effect on health outcomes by failing to reduce the parasite load or delaying treatment with high quality medicines, along with other possible long-run adverse effects.[7] Because poor quality medicines can contain sub-therapeutic amounts of the active pharmaceutical ingredients, the sale of substandard ACTs can also lead to the development of artemisinin resistance (WHO, 2011b).

The WHO recommends that all cases of suspected malaria should be confirmed using parasite-based diagnostic testing. However, due to lack of access to proper diagnostic technologies, symptomatic diagnosis (whether the individual has fever or not) is the norm in most of Africa. In most cases, the diagnosis is done by the patient or caregiver themselves without any professional assistance.[8] Diagnosis by symptoms alone, however, can be highly misleading. Many infectious diseases mimic malaria both in initial symptoms and in signs of severe illness. Reyburn et al. (2004), for example, find that more than half of the patients receiving treatment for malaria at government hospitals in Tanzania were actually not infected, and Cohen et al. (2012) show that only

[7] A 2006 systematic review of 18 studies concluded that untreated or inadequately treated *plasmodium falciparum* malaria during childhood affects short- and long-term neurocognitive performance (Kihara et al., 2006), and that through a higher risk of anemia, it also adversely impacts cognitive development (Shi et al., 1996). Recent estimates, based on quasi-experimental methods, also suggest a positive effect of malaria reduction on income and human capital attainment (Barecca, 2010, Barofsky et al., 2011; Bleakley, 2010; Cutler et al., 2010).

[8] Amexo et al. (2004) report that over 70 percent of malaria cases in Africa are diagnosed at home.

38 percent of adults who seek treatment for malaria at drug shops in Kenya actually have malaria.[9]

Misdiagnosis of malaria has a direct effect on households' health and socio-economic welfare, because individuals wrongly diagnosed with malaria will be unnecessarily exposed to the harmful side-effects of the drugs, and the true cause may be treated with delay or not treated at all, leading to prolonged and worsening illness. Misdiagnosis has also been shown to hamper social learning about the effectiveness of antimalarials (Adhvaryu, 2012).

In most of Africa, and, in particular, in rural areas and among poorer households, treatment of malaria is largely done at home using either traditional remedies or drugs bought from local shops. WHO (2011a), for example, estimates that 72 percent of those who seek treatment for febrile children in Africa seek treatment from private providers, with informal and unregulated private outlets being the most common. Studies on health-seeking behavior document similar patterns. Rutebemberwa et al. (2009), citing proximity and stock-outs as the main reasons, find that two-thirds of febrile children in a predominantly rural area in the Eastern region of Uganda were treated at home with drugs from informal drug shops and private clinics.[10]

Evidence from medical anthropology suggests that misconceptions about how malaria is transmitted and treated are common (e.g., Breman, 2004; Comoro et al., 2003; Kengeya-Kayondo et al., 1994). While it is well-known that malaria is caused by mosquitoes, most are not informed as to the specific mechanism for malaria transmission. In a study of women's perceptions about malaria in Uganda, for example, most respondents reporting that malaria is caused or transmitted by mosquitoes had an explanatory model that differed from the biomedical one (Nuwaha, 2002). Specifically, only a minority believed that malaria is transmitted through mosquito bites. A majority of the respondents instead held the belief that malaria is transmitted by drinking water with mosquito eggs or larvae. Interacting with somebody with malaria was also believed to be a common cause of malaria, and a significant fraction of the respondents also believed that eating fruits, such as mangos, infected with mosquito eggs is an important transmission channel.

If consumers attribute illnesses caused by bacterial, viral or parasitic infections to malaria, especially as many of these diseases often are self-limiting (meaning that patients recover quickly even in the absence of proper treatment), these misconceptions may lead consumers who quickly

[9]The high rate of malaria misdiagnosis and over-prescription of antimalarial treatment is driven by four factors. First, blood slide microscopy, considered to be the gold standard for malaria diagnosis in laboratory situations, is either not available or not used. Second, even when blood slide microscopy is available, it often has low accuracy in the field due to poorly maintained equipment, low supply of good-quality reagents, and lack of experienced and trained lab technicians (Amexo et al., 2004; Zurovac et al., 2006). Third, rapid diagnostic tests (RDTs), which have been shown to be highly accurate and can be performed by non-clinical staff or patients themselves, are either not available or too expensive for consumers to demand and use, particularly in rural areas (Cohen et al., 2012). Fourth, compliance with test results, both by individuals and health practitioners, is weak (Juma and Zurovac, 2011).

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

recover after treatment to incorrectly infer that drug quality is high.

2.2 Supply

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

Counterfeit and substandard quality is, however, not a problem specific to antimalarial drugs. The WHO estimates that annual earnings from substandard and counterfeit drugs were US$32 billion in 2003 (WHO, 2003), and Bate (2011) estimates that as much as 15 percent of the global drug supply outside of advanced countries is counterfeit. This figure rises to over 50 percent in certain markets in parts of Africa and Asia.

The extent of counterfeit and substandard medicines in circulation in Africa is linked to a variety of causes, not least of them a de facto largely unregulated pharmaceutical market where non-licensed drug 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 percent that of an authentic drug. The manufacturer cost of substandard drugs (i.e., drugs that are produced by the authorized manufacturer but do not meet quality specifications set by national standards) is one-half to two-thirds that of a high quality manufacturer. A decrease in costs can be achieved by using lower quality ingredients, under-dosing ingredients, cutting the processing time, or lowering hygiene controls.

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

The quality of an ACT drug is difficult to distinguish based on visual characteristics. This is

illustrated in Figure 1, which shows two packs and blister packages from two samples of ACTs we purchased and tested, one fake and one authentic. More systematic evidence is presented in Newton et al. (2011) and Dondorp et al. (2004). Newton et al. (2011), for example, conduct a blind study of the physical appearance and text on the packaging of counterfeit and substandard antimalarials from eight sub-Saharan African countries, compared with known authentic samples, and conclude that the packaging of counterfeit drugs is similar to that of genuine samples.

A strand of the theoretical literature on product quality suggests that, in equilibrium, even though product quality cannot be directly observed ex ante, the price will be higher for high-quality products (Shapiro, 1982; Wolinsky, 1983; Milgrom and Roberts, 1986).[11] Empirically, however, there is scant evidence on the relationship between quality and price in the pharmaceutical markets of developing countries. Bate et al. (2011) is an exception. Using data for several different types of drugs collected from 185 private pharmacies across 17 developing and middle-income countries, they reject the hypothesis that price is a monotone function of quality. Although drugs that fail quality tests are priced slightly lower on average, the price dispersion is so large that consumers cannot ensure the purchase of high quality through high price alone.

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

3 Learning, misconceptions, and quality in the market

Antimalarial medicine is an experience good, and thus consumers observe neither the quality of the medicine sold nor the utility it will yield before purchase. In markets for such goods, a firm's incentive to provide high-quality goods hinges on consumers' ability to learn about quality. In this section, we provide a simple two-period framework to illustrate how two constraints – lack of access to diagnostic testing and misconceptions about malaria – impede the quality learning process and in turn influence the sellers' incentives to provide high-quality medicines.

3.1 A simple framework

Consider a market with a continuum of identical consumers of unit mass. There are two periods. In each period, consumers fall sick with one of three diseases with similar symptoms (fever). A share

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

θ_t of the consumers contracts malaria, a share ω_t contracts some (in the short run) self-limiting non-malarial disease, and a share $1-\theta_t-\omega_t$ of the consumers contracts a non-malarial disease which is not self-limiting (in the short run). There are two possible malaria states, high (θ_H) and low (θ_L), with the low malaria state occuring with probability π. We assume that there is only one state of the self-limiting non-malarial disease, $\omega_t = \omega$, and that $\theta_H + \omega < 1$. Consumers know their symptom (fever), but because they lack access to diagnostic testing, they cannot tell what disease they are suffering from.

A consumer recovers quickly if she suffers from malaria and if she is treated with an authentic (high-quality) antimalarial. A consumer also recovers quickly, independently of treatment, if she suffers from a self-limiting disease. Let m_t denote the share of authentic (high-quality) antimalarials sold by the drug store in period t. Then, a share $\sigma_t = \theta_t m_t + \omega$ of the consumers that buy antimalarial drugs recovers quickly in period t. Consumers do not observe the malaria shock, θ_t, but they know the distribution of θ and observe σ_t at the end of period t. The problem facing consumers is to discern whether a given health outcome is due to outside factors (health shocks) or the quality of the antimalarial medicine.

We assume that treatment with antimalarial medicine generates two possible utility levels, normalized to 0 and 1. We assign a utility of 1 to the case where the consumer recovers quickly from malaria, and a utility of 0 when that is not the case. As antimalarial medicine is an experience good, consumers observe neither the quality of the pills sold nor the utility it will yield before purchase. The only issue for a consumer in period t is the probability she assigns to the drug inducing a positive outcome in that period. Let p denote the probability that the consumer recovers quickly from malaria. Then, $p_t = \bar{\theta}\rho_t$, where $\bar{\theta}$ is the likelihood of suffering from malaria, and ρ_t is the probability that the antimalarial medicine is authentic ($m = 1$). The normalization of utility levels means that p_t is also the expected utility of treatment with antimalarial medicine. For specificity, we assume that each consumer pays her expected utility amount for the medicine.[12]

In each period, the drug store sets the quality of the drugs (m). The cost of selling a share m_t of authentic drugs is cm_t, with $c > 0$. There are two possible types of drug shop owners, "honest" (H) and "opportunistic" (O), with superscript $T = \{H, O\}$ denoting type. An honest type always sets $m = 1$, while an opportunistic type sets m to maximize profits. Nature draws the type at the start of period 1, with the honest type chosen with probability ϕ. As the honest type makes no choices, our focus is on the opportunistic type. To simplify notation, the marginal cost is normalized to $c = \bar{\theta}\phi$.

The sequence of events is as follows. At the beginning of period 1, consumers assign a probability ϕ to the seller being honest, and have an expected utility p_1 from the antimalarial drug treatment. If the seller is opportunistic, she makes her unobserved quality choice. The market then

[12]The set-up here draws on Mailath and Samuelson (2001).

opens, and the seller receives revenues of p_1. Consumers next observe the share of people that recovered quickly, σ_1, and update beliefs about the type of seller and hence their expected utility in period 2 (p_2). We denote by $\varphi(\phi|\sigma)$ or ϕ_σ the posterior probability that the seller is honest, given a realized outcome σ and a prior probability ϕ.

To highlight possible mechanisms, we first consider a monopoly seller facing consumers with either a correct or a false biomedical model of malaria. We then consider how the introduction of a seller committed to high quality affects learning and thereby market outcomes.

Example 1: Consumers with a correct biomedical model for malaria

Suppose consumers know the correct biomedical model for malaria; i.e., they know that in a given period either a share θ_H or a share θ_L suffers from malaria. Consumers also know or can estimate ω.[13]

The solution concept is PBE. Denote the consumers' expectation of the sellers' choice of m_t conditional on type T as $\tilde{m}^T$. We solve the problem working backwards. Consumers realize that only an honest type will sell authentic drugs in the last period, as the seller's choice of m_2 has no effect on revenue but raises costs. Thus consumers face the problem of determining the likelihood that the seller is honest (ϕ_σ) given the realized outcome (σ_1) and expectations of m ($\tilde{m}^T$).

Proposition 1: *Suppose (i)* $(1-\pi)\phi_{\theta_L} - \phi\frac{\theta_L}{\theta_H} > 0$ *and (ii)* $1-(1-\pi)\phi_{\theta_L} - (1-\phi)\frac{\theta_L}{\theta_H} > \phi(1-\frac{\theta_L}{\theta_H}) > \pi\phi_{\theta_L} + (1-\pi)(1-\phi_{\theta_L})$*, where* $\phi_{\theta_L} = \frac{\pi\phi}{\pi\phi+(1-\pi)(1-\phi)}$*. Then there exists a unique pure strategy equilibrium with* $m^* = \tilde{m}^O = \theta_L/\theta_H < 1$*; i.e., a share of the drugs sold in equilibrium will be fake.*

Proof: See appendix. Conditions (i) and (ii) ensure that the seller's expected profit in equilibrium is positive and that no deviation from choosing m^* is profitable. Condition (ii) also ensures that the equilibrium is a unique pure strategy equilibrium and that the seller would want to commit to set $m = 1$ in period 1.

A Bayesian consumer realizes that, after accounting for ω, the only health outcomes consistent with the seller being honest are θ_H and θ_L. Thus, observing θ_L and expecting an opportunistic type to set $\tilde{m}^O = \theta_L/\theta_H$, the consumer cannot tell for certain whether the seller is honest and a share θ_L of the consumers suffered from malaria, or if the seller is opportunistic and a share θ_H suffered from malaria. Expected period 1 quality, as perceived at the end of period 1, is $\phi_{\theta_L} + (1-\phi_{\theta_L})\frac{\theta_L}{\theta_H}$. The seller faces a moral hazard problem. He has a short term incentive to choose low quality, but could earn higher profits by commiting to high quality. If conditions (i) and (ii) hold, the reputation gains are high enough to ensure that at least some drugs are authentic in equilibrium, but not high enough to sustain an equilibrium with high quality ($m = 1$).

[13] In a slightly more realistic model where some consumers do not buy antimalarial drugs, consumers could estimate ω by comparing the health outcomes of those that do not seek treatment (a share ω of which will recover quickly).

Example 2: Consumers with a false biomedical model for malaria

Suppose instead that consumers have misconceptions about the relationship between malaria and other febrile diseases. Specifically, assume consumers attribute (self-limiting) illnesses caused by bacterial, viral or parasitic infections to malaria. Instead of the correct model, $\sigma_t = \theta_t m_t + \omega$, consumers now assume that the share of consumers that recovers quickly is generated by the incorrect model $\sigma_t^f = \theta_t m_t + \epsilon$, where $\epsilon \sim U[0, \omega]$ is an unobserved random noise term.[14]

Proposition 2: *Suppose conditions (i) and (ii) hold. Then there exists a unique pure strategy equilibrium with* $\tilde{m}^O = \theta_L / \theta_H$ *and* $m^{**} = (\theta_L - \omega) / \theta_H < m^*$.

Proof: See appendix. Observing the share of people who recovered after treatment, σ, consumers with a false biomedical model fail to properly account for the fact that a share ω had a self-limiting disease and recovered regardless of drug quality. The seller can exploit these misconceptions by setting a lower quality without losing its reputation. As in Barberis et al. (1998), the consumers are Bayesian in their updating of expectations, although their biomedical model of malaria is inaccurate. Comparing examples 1 and 2, the posterior probability that the seller is honest (ϕ_{θ_L}) and consumers' expectation of the seller's quality choice ($\tilde{m}^O$) are identical, although $m^{**} < m^*$. These expectations, however, are consistent with outcomes when evaluated with the incorrect model $\sigma^f = \theta m + \epsilon$.[15]

Example 3: Entry by a seller committed to high quality

Consider now an extension of the set-up with an additional outlet that is committed to selling high-quality antimalarials. That is, let the seller be an honest type that mechanically sets $m = 1$. Given the empirical setting in this paper, we label the entrant an NGO.

The entry of a new seller committed to high quality raises a number of issues, including optimal price setting and reputation building strategies. We disregard these issues and simply assume that the two sellers are perceived as being identical in period 1.[16] In period 1, therefore, the decision whether to buy from the incumbent or the NGO is determined by a coin flip. In the experiment we discuss below, the NGO branded itself as a high quality seller by using the brand name of the funding organization, a large microfinance institution. It also entered the market selling antimalarial pills below the market price. It is reasonable to think that branding and subsidized prices influenced consumers' willingness to buy from the NGO, and that over time this helped the

[14]The addition of a random noise term is required to ensure that the belief that various self-limiting illnesses are malaria is consistent with observed outcomes.

[15]Note that the equilibrium outcome does not hinge on the assumption of a random noise term. In fact, provided that conditions (i) and (ii) hold, the equilibrium would be identical if the incorrect model was specified as $\sigma^f = \theta m$. Dropping the assumption of a random noise term, however, implies that if a seller sets $m = 1$, realized outcomes (σ) are inconsistent with the (incorrect) biomedical model consumers have in mind.

[16]We also assume that the incumbent seller can observe the type of the NGO. It is straightforward to relax this assumption.

NGO to build a reputation as a high quality seller. Here, however, we simply assume that half of the consumers buy from the NGO in the first period.

Proposition 3: *Suppose conditions (i) and (ii) hold and that consumers know the correct biomedical model for malaria. Then there exists a unique pure strategy equilibrium with the opportunistic seller setting* $m = \tilde{m}_I^O = m_I^* = 1$.

Proof: See appendix. With the new seller on the market, consumers are provided with additional information. Let σ_j denote the share of the consumers that recovered quickly in period 1 after getting treatment by antimalarials bought from outlet j. Given that the malaria shock is an aggregate shock, relative health outcomes are $\sigma_I/\sigma_{NGO} = (m_I\theta + \omega) / (m_{NGO}\theta + \omega)$, where subscript I $[NGO]$ denotes the incumbent [NGO]. If $\sigma_I/\sigma_{NGO} < 1$, $m_I < m_{NGO}$ and since honest types by assumption choose $m = 1$, it follows that the incumbent seller cannot be an honest type. Consumers' access to information on relative health outcomes constrains the seller's choice of m. Specifically, the seller now faces the choice of setting $m = 1$ and mimicking the NGO, or setting $m = 0$ and being revealed as opportunistic. Mimicking the NGO is optimal provided that the reputation gains outweigh the costs, which is the case if condition (i) holds.

Proposition 4: *Suppose conditions (i) and (ii) hold and that consumers have a false biomedical model for malaria. Then there exists a unique pure strategy equilibrium with* $\tilde{m}_I^O = 1$ *and* $m = m_I^{**} = (\theta_H - \omega) / \theta_H < 1$.

Proof: See appendix. The belief that various self-limiting illnesses may be malaria implies that consumers cannot observe realized outcomes, or at least not precisely. Specifically, consumers believe that any health outcome in the ranges $[\theta_H, \theta_H + \omega]$ and $[\theta_L, \theta_L + \omega]$ are consistent with the seller being honest. This imprecision is exploited by the incumbent who can sell lower quality antimalarial pills and still maintain a good reputation.

3.2 Implications and predictions

In summary, the model makes five key predictions on how the market for (potentially fake) antimalarial medicine works:

1. Consumer demand for antimalarials is decreasing in the subjective likelihood of fake drugs being sold by a seller.

2. Consumers with misconceptions about malaria overestimate the likelihood that they suffer from malaria. Conditional on actual quality, they expect fewer fake drugs and overestimate sellers' quality.

3. In expectation, as the share of consumers with malaria misconceptions increases, the quality of antimalarial medicine falls.

4. The entry of a seller committed to high quality increases the quality of the medicine sold by the incumbent seller. As actual quality increases, perceived quality increases and demand goes up.

5. In expectation, the increase in drug quality in response to the entry of a seller committed to high quality is decreasing in the fraction of consumers with misconceptions about malaria.

Intuition: Bayesian consumers learn about quality from observable health outcomes. Thus, in equilibrium, expected quality is increasing in actual quality, and demand for antimalarial drugs is increasing in consumers' beliefs about the sellers' quality choice. The entry of a seller committed to high quality provides consumers with additional information that can be used to assess quality. Provided that the cost of selling high-quality drugs is not too high, it is therefore optimal for the incumbent to mimic the NGO, and quality consequently increases. As actual quality increases, perceived quality also increases, and so demand goes up. In the model, consumers with misconceptions about malaria do not realize, or do not take into account, that a share ω of consumers suffers from fever due to other, self-limiting, infections. As a consequence, they overestimate the likelihood that they suffer from malaria, and conditional on actual quality they expect fewer fake drugs and overestimate quality. This bias is exploited by the seller and in expectation, drug quality is decreasing in the fraction of consumers with a false biomedical model. The entry of a seller committed to high quality provides consumers with additional information, but information on relative outcomes now provides only a noisy measure of relative quality choices. As a consequence, the incumbent's incentive to raise quality in response to the entry of a high quality seller weakens. In expectation, the increase in drug quality due to entry is decreasing in the fraction of consumers with an incorrect biomedical model.

In the following sections, we test these predictions in the context of an ongoing impact evaluation of a market-based community health care program in Uganda.

4 Setting and Design, Data, and Measurement

4.1 Setting and Design

To assess the predictions about how the market for antimalarial medicine works, we use both experimental and non-experimental data. Specifically, we combine two rounds of household survey

data from an ongoing impact evaluation of a market-based community health care program in Uganda with a cross-sectional dataset on drug quality.

The impact evaluation of the market-based community health care program in Uganda includes 214 villages (or clusters), organized into 10 branches, of which seven branches are managed by BRAC and three are managed by Living Goods.[17] For the drug quality study, three BRAC branches and the largest of the three Living Goods branches were selected. Each branch operates in a specific district, and all four districts (Bushenji, Mbale, Mbarara, and Mpigi) are characterized by high and endemic *P. falciparum* malaria prevalence (Figure 2). In total, there were 99 project villages in the four selected branches. For the experimental design, the villages were stratified by location (branch) and population size, thus creating matched blocks with similar characteristics. From each block, half of the villages were then randomly assigned to the treatment group (49 villages) and the remaining villages (50 villages) were assigned to the control group.

Once the treatment status was assigned, the collaborating NGOs (Living Goods and BRAC) recruited and trained a woman in each village to act as the sales agent for Living Goods and BRAC. The saleswomen work under an implicit piece-rate scheme. They are able to purchase authentic ACT antimalarials from the NGO at a 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. The saleswomen keep the difference, and the price charged is uniform across saleswomen within each organization.

The saleswomen are expected to sell ACTs to the particular households in the village to which they assigned, and are 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 NGO carries an ACT brand ("Lumartem") that was not sold in local drug shops during the period of the study. This enables us to rule out mechanical effects on market quality from the saleswomen selling directly to private outlets. The saleswomen also have access to other products they can sell, including hygiene products and other health products (such as deworming pills and painkillers). This should be kept in mind when interpreting our results [18]

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

[18] Since one would arguably not expect that the sale of hygiene products or deworming pills would affect either the quality of ACT antimalarials in drug outlets or household beliefs about the quality of ACTs in incumbent outlets, it seems unlikely that this would have a first-order effect on these outcomes.

4.2 Data

A baseline household survey and a census of drug shops were implemented in all 99 project villages at the beginning of 2010. The census verified the physical presence of all drug shops in the project villages. In total, 135 drug stores in 57 village markets were identified: 55 drug stores in 26 treatment villages and 80 drug stores in 31 control villages.[19] At the end of 2010, approximately 9 months after the intervention had begun, the drug quality survey was implemented in all villages. The drug quality survey identified 122 of the 135 stores.[20] Of the 122 shops, 93 stores in 47 villages had ACT medicine in stock at the time of the survey. The sample of outlets with drug quality data thus consists of 93 drug stores in 47 villages, of which 57 stores are located in 27 control villages and 36 stores are located in 20 treatment villages. A follow-up household survey was conducted in the fall of 2011, approximately 18 months into the intervention, in a subset of 48 randomly selected project villages.

4.3 Measurement

The measurement of drug quality had two main components: the purchase of ACT medicine and the testing thereof. For the former, we trained a set of enumerators with knowledge of the local area and language on how to use a prepared script when approaching the outlet. According to the script, the covert shopper was buying medicine for her sick uncle.[21] The covert shopper described the age of the uncle (48), symptoms common for malaria, and that she wished to purchase Coartem. Although Coartem is an ACT brand name, the term is commonly used for artemisinin-based combination therapy drugs.[22] After the purchase was completed, and once out of sight of the outlet owner, the surveyor recorded the drug price. The samples were then transferred to Kampala. To prevent deterioration, we followed standard procedures and kept the drugs away from light in a dry and cool place.

Chemical analyses of medicines like ACTs can be performed using several techniques (see e.g., Nayyar et al., 2012). Our method of quality testing was Raman spectroscopy, using a TruScan handheld scanner. The TruScan scanner illuminates a sample (pill) with a laser beam and measures the reflecting Raman spectra. The Raman spectra provide a fingerprint by which the

[19] The design, with 57 clusters, 2.4 drug shops per cluster, and an intra-cluster correlation coefficient of 0.2, had a power of 80 percent to detect a 0.47 standardized effect at the 0.10 significance level. It had a power of 60 percent to detect a standardized effect size of 0.36.

[20] The remaining 13 stores were either permanently or temporarily closed.

[21] To avoid having the covert shopper provide false and possibly sensitive information about her own child when making the purchase, the script was designed to deal with the shopper's sick uncle.

[22] In only two cases did the outlet sell multiple brands of equivalent active ingredients and strength. In these cases, the covert shopper acquired the least expensive brand.

molecule composition of the sample can be identified. The fingerprint is then tested against an authentic reference sample, and if they are sufficiently similar, as given by a probabilistic algorithm, the sample passes the test and is considered authentic.[23] An important advantage of Raman spectroscopy compared to laboratory methods is speed. Another important advantage is that compared to laboratory testing, which requires a fairly large set of pills to test, and thus would require multiple purchases or the purchase of more than one dose of tablets, the TruScan method provides a quality indicator per tested tablet. Methods comparing Raman spectroscopy to traditional laboratory methods have found a high degree of consistency across methods, and the Raman method is therefore viewed as suitable when conducting field studies (Bate et al., 2009).[24] We tested six pills from each drug shop sample, for a total of 558 tested pills.

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 cardboard used for the box, characteristics of the text on the box and blister pack, type and presence of holograms, etc.), ten surveyors visually inspected each sample and made an assessment of whether they believed the drugs were fake or not. Individual samples were sequentially presented (without any additional information), and the inspectors' assessments were reported after each sample.

To measure households' beliefs about the quality of antimalarials sold by 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" to "yes, all of them", via "yes, a few of them" and "yes, most of them". We create a binary variable "*Believes drug shop sells fake drugs*", defined by whether the respondent answers that at least some fake drugs were sold.

In the model, consumers with misconceptions about the biomedical relationship between fever and malaria overestimate drug quality, which affects demand and equilibrium quality. To measure such misconceptions, we asked respondents regarding their beliefs about malaria transmissions. This included whether malaria could be spread from mosquito bites, direct contact with someone who has malaria, or eating infected food (mangos). Since mosquito bites are the biological vectors through which malaria is transmitted, only the first transmission mechanism is correct. Direct contact with someone who has a fever or intake of contaminated food can lead to bacterial or viral infections which in turn cause fever, but not malaria. We create a dummy variable "*HH with malaria misconceptions*" equal to one if at least two of the respondent's answers are incorrect.

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

[24] According to the TruScan producer, nine out of the ten largest pharmaceutical companies worldwide rely on TruScan to authenticate inputs at their factories. 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.

To measure demand and treatment behavior, we asked about treatment of children reported sick with malaria in the last month, including the source of the medicine, type of antimalarial drug bought, and number of tablets acquired.[25]

4.4 Empirical Strategy

To assess the predictions about how the market for (fake) antimalarial medicine works, we use both experimental and non-experimental data. We first present summary statistics and simple correlations, using household survey data from the baseline survey and data on drug quality from the control villages. We start by establishing a set of facts on the prevalence of fake drugs, the unobservability of quality, and the prevalence of misconceptions about malaria among consumers. We then look at simple correlations to assess whether consumers are aware of the problem of fake drugs, whether they can infer quality at least partially, and whether demand for ACT drugs is increasing in consumers' beliefs about high-quality medicine as predicted by the model. We also assess whether the predictions related to biomedical misconceptions about malaria are consistent with the evidence – i.e., whether consumers with misconceptions about malaria overestimate quality and whether the likelihood of drug shops selling fake drugs is higher in villages with widespread misconceptions.

We then exploit the experimental variation in the data to assess how consumers, and the incumbent sellers, react to the entry of an NGO selling authentic ACT drugs at prices below those found in local markets. We use OLS to estimate the following specification

$$y_{ovd} = \beta NGO_v + \lambda_d + \gamma X_{vd} + \varepsilon_{ovd}, \tag{1}$$

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 a door-to-door NGO saleswoman selling authentic ACT drugs. For increased precision, we also report a specification including baseline village covariates X_{vd}, namely the share of household heads with secondary and tertiary education, the share of households with electricity or radio, a dummy indicating Muslim denomination, the average number of children per household, and the number of drug shops. The randomization was stratified at the district level, hence we include district fixed effects λ_d.

For a subset of variables we can also stack the pre and post data and explore the difference-in-

[25]There is no direct translation for the word "malaria" in the local languages, but rather a set of words to describe it. The enumerators used the most common phrase "omusujja gwa malaria" ("fever caused-by malaria" in direct translation) in the Luganda speaking areas and equivalent translations in the other local languages.

differences in outcomes; i.e., we estimate

$$y_{ovdt} = \beta_1 NGO_v + \beta_2 POST_t + \beta_3 POST_t \times NGO_v + \lambda_d + \gamma X_{vd} + \varepsilon_{ovd} \quad (2)$$

where $POST$ is an indicator variable for the post-intervention period and β_3 is the difference-in-differences estimate.

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

$$fake_{ovd} = \beta NGO_v + \theta Misconceptions_v + \eta(NGO \times Misconceptions)_v + \lambda_d + \gamma X_{vd} + \varepsilon_{ovd}, \quad (3)$$

where $fake_{ovd}$ is the failed quality test, and $Misconceptions_v$ is the share of households in village v with misconceptions about malaria, as measured in the baseline household survey. If incorrect beliefs hamper learning (prediction 5), then $\theta > 0$ and $\eta < 0$.

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

5 Results

5.1 Summary statistics and correlations

Prevalence of fake drugs

How common are counterfeit and substandard ACTs? Table 1 provides summary statistics of the prevalence of fake drugs in the control group. 36.8 percent of the outlets sell fake ACTs.[26] The prevalence is highest in the western, and most rural, districts (Bushenyi and Mbarara), and the prevalence is lowest in the district closest to the capital Kampala (Mpigi). Overall, 19.4 percent of all drugs fail the authenticity test. This number, however, includes data from outlets where all the tested samples passed the test. When conditioning the sample on outlets where at least one sample (pill) failed the authenticity test, 51.5 percent of the tested ACT drugs fail.[27]

[26] We also tested ACT quality from samples bought from 10 NGO saleswomen. All pills passed the authenticity test.

[27] It is plausible that our results in Table 1 provide a lower bound since the covert shoppers were asked to purchase a package of ACTs. Buying less than a full dose of ACTs when seeking treatment is a common practice. As the patient or caregiver will then have to judge the quality by only observing the blister package or single tablets, cheating should become easier.

The last rows in Table 1 report the prevalence of fake ACTs conditional on the market structure in the villages. In both villages with a monopoly seller and in villages with more than one drug store in the village market, fake ACTs are common.

Observability of drug quality

A key assumption in the model is that quality cannot be directly observed. To test this assumption, we use data from a visual inspection of the samples. Specifically, ten surveyors were asked to visually inspect each sample and make an assessment of whether they believed the drugs were fake or not. To set prior beliefs in a manner approximately consistent with the data, the inspectors were informed that thirty percent of the samples were fake. As reported in columns 1-2 of Table 2, there is little evidence that observable characteristics can reveal quality. While the coefficients are positive, the point estimates are small and not statistically significant at conventional levels, indicating that it is difficult to infer quality solely based on observable characteristics.

In the model, drug stores set quality but not prices. A strand of the theoretical literature on product quality, however, suggests that prices function as a signal of quality; i.e., in equilibrium the price will be higher for high-quality products (Shapiro, 1982; Wolinsky, 1983; Milgrom and Roberts, 1986). Columns 3-4 present estimates on the relationship between price and quality in the control villages. By using village fixed effects, we exploit variation across drug shops within the same local market, thereby essentially holding demand (e.g., malaria prevalence, income, and expectations of quality in the village) and supply factors (e.g., transportation costs and degree of competition in the village) constant within a local market. Column 3 shows the correlation from a bivariate regression using a dummy variable indicating whether the outlet sells fake drugs (1) or not (0), while column 4 uses the share of drugs that are fake. As evident, variation in prices within a given local market does not signal differences in quality.[28]

Household beliefs and quality of drugs

Are consumers aware that fake drugs are sold? Do consumer beliefs matter? In the baseline household survey, 26 percent of households report they believe their nearest drug shop sells fake antimalarials. Figure 3 uses data collapsed at the district level and relates beliefs about drug quality to measured drug quality in the control villages. Households are more suspicious of fake drugs in districts where a higher fraction of the tested drugs fail the authenticity tests. The correlation coefficient between beliefs and actual quality, while positive, is however low (0.09-0.10), indicating that learning about drug quality is noisy (results not shown for brevity). Furthermore, the data provides suggestive evidence that households tend to underestimate the prevalence of fake

[28]There is significant variation in drug quality across shops within the same village, as village fixed effects alone explain only 36 percent of the variation in the share of fake drugs in the data. In addition to the benefits mentioned above, the approach of using within-village variation is arguably more relevant from the perspective of a potential trade-off between quality and price for households. Regressions without village fixed effects confirm there is no positive correlation between quality and price (the point estimate is negative; result available upon request).

drugs. Specifically, 34 percent of households predict that there are no fake drugs sold although they live in villages where at least some of the covert shopper samples fail the authenticity test. Perhaps more strikingly, 31 percent of households believe there are no fake drugs sold when there is a substantial prevalence of fakes (more than 20 percent failed samples). By contrast, only 13 percent of households report that they believe fake drugs are sold in villages where none of the pills fail the authenticity tests (see appendix Table A.4.). In the absence of measurement error, these numbers would reflect the prevalence of type II and type I prediction errors by households. Of course, although the Raman Spectroscopy test itself is precise, these results may in part be due to various forms of measurement error. For example, since drug shop behavior may have changed between the measurement of households' subjective expectations in the baseline survey and the measurement of actual drug quality in the covert shopper data, the predictions may have been more accurate than the data suggest. Also, it is not uncommon to have multiple shops in a village. It is worth noting, however, that the results are similar if we restrict the analysis to villages where there is only one drug shop.[29]

More importantly, one of the hypotheses pursued in this paper is that knowledge about malaria plays a key role in shaping beliefs about whether a drug shop is selling fake drugs, which in turn affect shop incentives to provide quality. In the model, consumers with misconceptions about malaria overestimate the likelihood that they suffer from malaria and underestimate the prevalence of fake drugs. With a higher share of households with such beliefs in the market, in turn, drug quality will be adversely affected. In the baseline data, essentially all of the respondents (99 percent) correctly answer that malaria can be caused by mosquito bites. 52 percent of the respondents, however, also report that malaria can be caused by direct contact with someone who is infected with malaria, and 60 percent believe that eating infected food can cause malaria. False beliefs about what causes malaria are thus common. In the full sample, 34 percent of the households are estimated to have severe misconceptions, defined as answering at least two questions incorrectly.[30]

Using baseline household survey data, panel A of Table 3 investigates how these misconceptions are correlated with self-diagnosis of malaria, treatment behavior, and beliefs about drug quality. Households with misconceptions about malaria are on average 16 percent (6.6 percentage points) more likely to report their child was sick with malaria in the last month, and 13 percent (5.1 percentage points) more likely to treat their child for malaria. Of course, these estimates do not control for actual malaria prevalence and should be interpreted with caution. However, the

[29]Results not shown for brevity, but are available upon request.

[30]Since nearly all respondents got the mosquito question right, the variable essentially captures whether the respondent believed direct contact and food were transmission channels. It thus captures severe misconceptions, as compared to just getting one question wrong. Also, in the model, these misconceptions reflect having the wrong biomedical model. It is possible that the questions capture subjective *uncertainty* about which biomedical model, or transmission channel, is the correct one. The latter approach is essentially isomorphic to the former, since both would tend to lead to noisier learning and underestimation of non-malarial fever.

estimate in column 3 shows that children are no more likely to have experienced fever with cough (a strong predictor of malaria) during the same time period, which alleviates some of the concern that children of parents with misconceptions are more likely to truly be sick in malaria.

Comparing across households facing the same drug shops and average quality in villages (i.e., using village fixed effects), columns 4 and 5 show that households with misconceptions are significantly less likely to believe the nearest outlet sells fake antimalarial drugs. The estimates are significant whether one uses a binary dependent variable and OLS, or the likert scale and ordered logit. The estimated magnitude is non-trivial, and implies that misconceptions are associated with a 30 percent (7.6 percentage points) lower subjective likelihood of fake drugs.[31] However, this does not necessarily imply that misconceptions are associated with overestimation (or underestimation) of quality. In columns 6 and 7 we match household predictions with actual quality from the drug quality survey to test whether misconceptions are systematically associated with false predictions (positive or negative). We find no evidence that misconceptions lead to more false household predictions of positive levels of fake drugs when there are no fake drugs sold in control villages (column 6). There is, however, evidence that misconceptions lead to underestimation of the prevalence of fake drugs. The estimated coefficient in column 7 implies that households with misconceptions are 22 percent (6.8 percentage points) more likely to predict there are no fake drugs when in fact there is a substantial fraction of fake drugs (defined as more than twenty percent failing the authenticity test) according to our drug quality survey.[32] It is worth noting that the estimates are essentially identical without the household covariates (appendix Table A.5), suggesting that the results are not simply driven by unobserved differences in socio-economic characteristics across households with and without misconceptions.

Do drug shops exploit consumers' misconceptions as the model predicts? Using the drug shop data matched with average village beliefs about malaria, in panel B of Table 3 we estimate whether the prevalence of misconceptions about malaria in the village is associated with worse drug quality. The results show that drug shops are more likely to sell fake drugs in villages where misconceptions are more common. The correlations remain significant and become stronger when controlling for average education, wealth proxies, and degree of competition (number of drug

[31]There is no significant difference in beliefs about the effectiveness of ACT drugs, or the effectiveness of non-ACT antimalarial drugs (appendix Table A.5). Thus, the results are seemingly not confounded by beliefs about the effectiveness of authentic drugs, but appear to capture the subjective likelihood of fake drugs. Also, beliefs about quality of the drug shops are negatively associated with ACT treatment from private drug shops (appendix Table A.6), consistent with the implication of the model that quantity demanded is increasing in expected quality.

[32]We use a cutoff of twenty percent failing to minimize the likelihood that the dependent variable suffers from measurement error in type II errors. The estimate is qualitatively and quantitatively very similar if we use a zero percent failing cutoff, however, indicating that any measurement error is uncorrelated with misconceptions. Also, the point estimate increases in magnitude if we restrict the data to villages with only one drug shop, which suggests that measurement error due to multiple shops is unlikely to drive the association (results not shown for brevity but are available upon request).

shops). A one standard deviation (15.2 percentage points) increase in the share of consumers with misconceptions about how malaria is transmitted is associated with a 21 percentage point higher likelihood that an outlet sells fake drugs (column 9), and a 13 percentage point increase in the share of fake drugs sold (column 11).

Interpretation

The results discussed above are simple correlations. Interpreted through the lens of the model, however, they provide suggestive evidence of how the local markets for antimalarial medicine work: fake ACT drugs are common, with substantial spatial variation across local markets. Observable characteristics and prices do not reveal quality, at least locally, indicating that beliefs about drug quality will crucially depend on how consumers infer quality based on experience and health outcomes. 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 these optimistic consumers also appears to have consequences for drug quality, as drug shops sell more fake drugs in markets where misconceptions are more common. This finding is consistent with the hypothesis that the quality of experience goods is lower in markets where consumers find it more difficult to infer quality based on experience or outcomes.

5.2 Experimental evidence

In this section, we exploit experimental variation to shed further light on how the market for antimalarial medicine works. Specifically, we use data from an ongoing impact evaluation where an NGO exogenously entered villages selling authentic ACT drugs below prevailing market prices. We first present results on how the entry impacted the competing outlets' quality choices and consumers' quality expectations. We then investigate whether the NGO entry effects resulted in differential impacts on quality conditional on the share of consumer with malaria misconceptions, as predicted by the simple model in section 3. We then assess the effects on prices and quantities.

In the model, incumbent drug outlets will respond to competition from the NGO by increasing quality, i.e., a change on the intensive margin, if $c \leq \bar{\theta}\phi$. If the cost of providing high quality is too high, however, competition will result in exit by the incumbent outlet. To incorporate potential changes both on the intensive and extensive margins, we present results using three experimental samples. Our core sample consists of all 135 drug shops identified at baseline (the 57-villages sample). In this sample, we can measure changes both at the extensive (exit of drug shops from the market for ACTs) and the intensive margin (changes in behavior by remaining outlets). We also report results for the sample of 93 drug stores (the 47-villages sample) for which we have both price and quality information from the drug quality survey. If exit is uncorrelated with assignment to treatment, estimation of equation (1) using the 47-villages sample will give unbiased estimates

of changes in the intensive margin. As a robustness test, we also use the 99-villages sample (i.e., we include villages with no drug shops at baseline) for the key outcomes, in which case we then collapse the data to the village level.

Pre-intervention differences

Table A.1 reports mean pre-treatment characteristics for both groups, along with test statistics for the equality of means. There is no systematic difference between the treatment and the control group at baseline. Thus, the random assignment of villages was successful. Panel A uses the full sample of 99 villages. Malaria morbidity among children under 5, here defined as share of children reported to have fallen sick with malaria in the last month, is 43 percent in the treatment group (41 percent in the control group), and 41 percent (37 percent in the control group) of these children were reported to have been treated with ACTs. Most households (60 percent in the treatment and 58 percent in the control group) buy their ACT drugs from private drug shops. ACT drugs are believed to be highly effective, although non-ACT drugs, including Chloroquine, Quinine, and SP, are also viewed as being effective by most households in both groups.[33] 28 percent (26 percent in the control group) of the households believe the nearest drug shop sells fake antimalarial drugs and 34 percent (38 in the control group) of the households incorrectly believe that direct contact with someone who has a fever and intake of contaminated food can cause malaria. The average village size is 193 households (191 in the control group), and while the share of villages with at least one private drug outlet and the number of private drug outlets are slightly higher in the control group, the differences between the groups are not statistically significant. Panel B uses data from the sample of 57 villages with drug shops at baseline. The means are similar to the full sample, and balanced across treatment and control villages on essentially all outcomes.

Effects of NGO entry: Quality in drug shops

Table 4, columns 1-2, use the sample of 57 villages with drugs shops at baseline. Consistent with prediction 4, having an NGO outlet in the local market decreased the likelihood of an incumbent drug shop selling fake ACTs by 15-18 percentage points. The effect is large in magnitude, considering that the control group mean is 0.26. We find an effect of the same order of magnitude, albeit somewhat less precisely estimated, when using the sample of all 99 villages (as reported in appendix Table A.3, columns 1-2).[34]

Columns 3-6 of Table 4 use data for the 93 drug shops for which we have both price and quality information from the drug quality survey (i.e., shops that stocked ACT). Consistent with the findings reported in columns 1-2, the results show that the intervention increased the quality in

[33] The fact that chloroquine is viewed as being effective, despite the high rate of chloroquine resistance, again points to a noisy learning environment. Frosch et al. (2011) estimate a chloroquine resistance in Uganda of nearly 100 percent.

[34] In the 99-villages sample, 42 villages did not have a drug shop within the village boundary at baseline. Thus, the intervention could not influence incumbent behavior in about 40 percent of the villages in this sample.

incumbent drug shops. Having an NGO outlet in the local market decreased the likelihood that an incumbent drug shops sells fake ACTs by 20-21 percentage points (columns 3 and 4). Columns 5 and 6 show that the share of fake drugs in incumbent drug shops decreased by 11-13 percentage points. From a baseline of 19.4 percent, this implies that the prevalence of fake drugs dropped by more than fifty percent, corresponding to a standardized treatment effects (β/σ) of about one-half.

The results in columns 1-6 are consistent with effects on both the extensive and the intensive margins. If market exit is random, the estimates in columns 3-6 would capture changes in quality on the intensive margin only. A simple attrition check shows that exit is not systematically associated with the NGO entry.[35] Similar exit rates, however, do not preclude that exit is selective. For example, if a significantly higher share of low quality outlets are pushed out of the market due to the NGO entry, while more high quality outlets exit in the control villages, exit rates could be similar and the results in columns 3-6 would capture changes both at the extensive and intensive margins. To assess whether there is evidence of selective exit, Table A.2 compares villages with and without drug shops during the drug quality survey, for all villages that had drug shops at baseline. Panel A shows that villages do not differ systematically at baseline, at least along observable dimensions. The only statistically significant difference is in the number of drug shops at baseline. That is, the likelihood that at least one outlet stocks and sells ACTs in the village at any given time (i.e., during our drug quality survey) is lower in villages with fewer outlets at baseline, which is expected. Panel B compares baseline characteristics for the treatment and control group using the sample of villages with drug shops at the time of the drug quality survey. The means are balanced across treatment and control villages on all outcomes. Thus, exit does not appear to be systematically correlated with assignment to treatment (panel B) and villages that experienced a change in the measured number of drug stores selling ACT medicine are not systemically different from villages that did not (panel A). Although suggestive, these results indicate that the entry effect on quality appears to be primarily driven by changes on the intensive margin.[36] Importantly, this finding also rules out that drug shops sell poor quality drugs because they cannot access, or cannot

[35]Table A.3 in the appendix, columns 5-6, reports the treatment effects on exit. In column 5, the dependent variable is an indicator variable taking the value 1 if the outlet was identified at baseline but was not open for business at the time of the drug quality survey, while in column 6, the dependent variable is an indicator variable taking the value 1 if the outlet was identified at baseline but did not sell ACTs at the time of the drug quality survey. While there is evidence of exit or attrition from the local markets – 11 percent of the outlets were not open for business and 28 percent did not sell ACTs at the time of the drugs quality survey in the control villages – it does not appear to be systematically correlated with the assignment to treatment.

[36]As an additional test, Table A.3, columns 3-4, reports the estimates of equation (1) using the subsample villages with no change in market structure, i.e., for the subsample of villages with no exit. Having an NGO outlet in the local market decreased the likelihood that an incumbent drug shop sells fake ACTs by 26 percentage points; i.e., a larger effect than in the full sample of drug outlets (Table 4). Column 4 shows that the share of fake drugs in incumbent drug shops decreased by 10 percentage points. This effect is similar to the one reported for the full sample (Table 4, columns 5-6) although the point estimate is less precisely estimated in this smaller sample.

afford, authentic medicine.[37]

Effects of NGO entry: Expectations of quality in drug shops

Table 5 presents difference-in-differences estimates of how the entry of the NGO affected the reputation of incumbent outlets. First, the post-survey dummy estimates indicate that households in general (i.e., in control villages) became more suspicious over the 18 month period between the two surveys. This may reflect an increase in overall awareness of the existence of counterfeit and substandard drugs (e.g., due to an increase in mass media's attention to the problem), or, potentially, a general increase in the actual prevalence of fake drugs over time. More importantly, since treatment villages would have had the same trend in beliefs in the absence of the NGO entry, the difference-in-differences approach estimates the average causal effect of NGO entry on households' subjective likelihood of fake antimalarials in incumbent drug shops. Using data from villages with shops at baseline (columns 1-3) or villages with shops selling ACT during the drug quality survey (columns 4-6), the difference-in-differences estimates show that NGO entry reduced the subjective likelihood by 11-13 percentage points. Thus, the decrease of fake drugs in outlets was accompanied by an improvement in reputation, consistent with learning.[38]

Why did the NGO entry affect both average quality and the reputation of drug shops? Interpreted within our simple theoretical framework, there are two complementary mechanisms that produce this effect. Firstly, when the NGO enters and is committed to selling high-quality drugs, learning about quality is less noisy, as it easier for consumers to detect when a drug shop sells low quality drugs (by comparing health outcomes for drugs from the NGO with outcomes for drugs from the outlet). In this sense, reputation forces are stronger. Secondly, if the first mechanism is sufficiently strong, the incumbent improves quality in order to not lose customers. Higher quality, together with a less noisy learning environment, leads consumers that are able to infer quality (partially or fully) to revise their posterior expectations upward.[39]

Heterogeneous entry effects: Malaria misconceptions

We argue that consumers' ability to detect low quality is a key reason for why incumbent outlets increase drug quality when the NGO enters. If this assumption is correct, we should expect smaller effects of entry on quality in villages with widespread misconceptions about malaria. Using the 47-villages sample for which we have price and quality data, Table 6 reports the estimated interaction

[37] See robustness discussion in section 5.3. If some sellers cannot access, cannot afford, or do not know the quality of the drugs they sell, competition from a high quality entrant may push these seller out of the market; i.e. an effect on the extensive margin, and result in higher average quality among remaining sellers.

[38] The effects are similar when restricting the sample to only those villages that were sampled at both baseline and endline, see appendix Table A.7, column 1. In appendix Table A.7, columns 2-3, we also report the estimates using endline data only. The point estimates are significant at the five and one percent levels, although somewhat smaller in magnitude.

[39] These mechanisms are not only consistent with the predictions of the simple model in section 3, but broadly consistent with the learning and reputation models in Shapiro (1982) and Mailath and Samuelson (2001).

effect of NGO entry and prevalence of misconceptions in the village at baseline. The interaction coefficients in columns 1-2 and 5-6 are positive and significant at conventional levels, implying weaker treatment effects when misconceptions are highly prevalent. The estimated magnitude implies that when the share of consumers with misconceptions is one standard deviation above the mean, there are no improvements in quality when the NGO enters.

Since misconceptions are not randomly assigned, one concern with these results is that the weaker treatment effects on quality reflect differences in socio-economic characteristics across villages, rather than truly weaker effects when consumers have difficulties in inferring quality due to these misconceptions. To address this concern, columns 3 and 6 add interactions between entry and household characteristics as additional controls. The point estimates are similar with these additional controls (and significant at the ten and five percent levels, respectively), suggesting that differences in socio-economic characteristics do not drive the results. Together with Table 3, and consistent with the model, these results indicate that low quality tends to prevail in markets where consumers face difficulties inferring quality.[40]

Effects of NGO entry: Price and Quantity

In the model, sellers set quality but not prices. The experimental variation we exploit, however, involved entry of a seller committed to selling authentic ACT drugs at prices below those prevailing in the local market. To assess the prediction on demand, we therefore first look at the impact on the incumbent sellers' price setting behavior.

Using the covert shopper data, columns 1-4 of Table 7 show that the entry of the NGO resulted in a fall in the average price of ACTs in incumbent drug shops by approximately 15-20 percent (from an average baseline price of 8910 Ugandan shillings in control villages to approximately 7000-7500 Ugandan shillings in the treatment villages). As the price of ACTs 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 0-6 percent. Since the intervention led to lower prices and increased quality, it follows that local drug markets were characterized by a substantial prevalence of low quality products accompanied by considerable mark-ups.[41]

[40] Note that the NGO entry coefficients in columns 3 and 6 reflect the the treatment effect when all the interaction coefficients are equal zero (which has no intuitive interpretation). Note further that that there is no clear heterogeneous treatment effect prediction on perceived quality. On the one hand, an increase in quality will lead households to revise expectations upward, although less so for households with misconceptions. On the other hand, if households with misconceptions have upward biased priors, as the model assumes and the results in Table 3 indicate, a less noisy learning environment due to NGO entry can lead to downward revised expectations. Moreover, the treatment effect of entry on actual quality is lower in villages with widespread misconceptions, so the typical household with misconceptions will revise expectations upward to a lesser extent than the typical household without misconceptions.

[41] As reported in appendix Table A.8, there is no evidence that the treatment effect on prices depends on the share of consumers with misperceptions about malaria. This is not surprising, at least according to our framework, since the mechanism that drives prices down is primarily the increased competition from the NGO, independently of consumers'

Table 8 estimates the effects on ACT quantity using data from the household survey on treatment of children reported sick in malaria.[42] Columns 1-3 show that there is no evidence of entry affecting the likelihood of sick children being treated with ACTs (the extensive margin), as compared to treatment with non-ACT antimalarials.[43] The entry of the NGO, however, affected the intensity of ACT treatment.[44] Conditional on ACT treatment, households acquired more pills to treat the child (columns 4-6). The effect is substantial in magnitude. According to the most conservative estimate, in treatment villages households acquired 2.45 more pills per sick child. From a baseline of 6.7 pills in control villages, this implies an approximate 37 percent increase in ACT quantity.[45] This suggests that the NGO entry increased the total size of the market for ACTs. Perhaps unsurprisingly, columns 7-9 further show that the increase in ACT quantity is not driven by sourcing from private drug shops.

Together, the evidence suggests that private drug shops lost market share when the NGO entered, but that their total quantity sold was not particularly affected. This result is arguably due to a combination of market forces. First, due to increased competition from the NGO, the inverse demand curve facing drug shops would have shifted inward (lower demand). Second, if quantity demanded is increasing in expected quality, since the expected quality of drug shops increased, the inverse demand curve facing drug shops would have shifted outward (higher demand). Third, due to a lower price in drug shops, there would have been movement down the inverse demand curve (higher quantity demanded). The results in Table 8 suggest that these demand forces approximately canceled each other out.

Finally, these results suggest that the welfare consequences of the NGO entry in the retail ACT market are relatively clear. With lower equilibrium prices, higher quality, and largely unaffected quantity, it is reasonable to conclude that producer surplus (drug shop profits) decreased from the entry. With higher quality and lower prices, consumer surplus arguably increased (directly due to the NGO selling authentic drugs at lower prices, and indirectly due to the externality effects on drug shops' quality and prices).[46]

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ability to infer quality.

[42] No data was collected on treatment of adults.

[43] The types of drugs used are: ACT (67 percent), Quinine (27 percent), Fansidar/SP (4 percent), and Chloroquine and other (2 percent).

[44] It is common practice to buy less than a full dose, and outlets typically offer a price per pill.

[45] The results are very similar using endline data only (appendix Table A.7).

[46] It is worth noting that the NGO sells their products to the saleswomen at a small but positive mark-up above the wholesale cost, and that the retail price is set so that the saleswomen have a small mark-up as well. Of course, marginal profit is not the same as producer surplus, and for a complete welfare analysis one would need to include the fixed cost for the NGO.

5.3 Alternative mechanisms

Although the experimental results are consistent with predictions 4 and 5, the findings do not rule out other explanations. Is it possible that the entry of the NGO affected quality on the market and consumers' expectations through another channel than the one we propose above? For example, through health education, the NGO saleswomen may have improved households' ability to diagnose malaria, or improved households' ability to draw inferences about drugs after taking them. A priori, this does not seem like a likely channel. Post-treatment, only two percent of the households report that they have attended a health education session during the last month. Moreover, the new saleswomen did not have access to any diagnostic tests, so the rate of misdiagnosis would likely not be influenced by the intervention. The self-reported rate of malaria is also similar across the treatment and the control groups. In appendix Table A.9 we report treatment effects on knowledge about malaria transmission and knowledge about antimalarial medicine. For all seven outcomes, the point estimates are close to zero and insignificant.Thus, health education does not seem to explain the findings.[47]

Another potential mechanism would be that the NGO informed households about the prevalence of fake drugs in the local drug stores, and/or put pressure on the drug shops directly to stop selling fake drugs. This too seems like an unlikely channel, as the NGO saleswomen, just like their customers, could not directly assess the quality of the antimalarial medicines sold by the incumbent drug stores. There is also no direct or anecdotal evidence that the NGO was involved in such activities.

Yet another possibility would be that the NGO saleswomen somehow influenced private drug shops' ability to (illegally) get hold of high-quality subsidized ACTs from public clinics. There could also be a mechanical effect on market quality from the saleswomen selling directly to the outlets. Both mechanisms could explain the increase in quality and the reduction in prices. There is no evidence, however, that these mechanisms are at play. A trivial fraction (2 percent) of the pills purchased in the drug shops in the treatment villages were of the brand "Lumartem", which is the brand carried both by the public clinics and the NGOs at the time of the survey.

In our model, the incumbent seller knows and sets quality. It is possible, however, that the sellers also face uncertainty about the quality they purchase from wholesalers. When faced with competition from a high quality entrant, it could then be the case that drug stores that unknowingly sell low quality ACT medicines are pushed out of the market. While we cannot fully rule out that this is the case, the treatment results are difficult to explain without assuming the drug shops have

[47] It is worth noting that there are no effects on the likelihood that households believe authentic ACT are effective. First, this is unsurprising, as 95 percent of households in control villages already believe so. Second, and more importantly, this suggests the effects in table 5 on the subjective likelihood that incumbents sell fake drugs are not confounded by effects on beliefs about the effectiveness of authentic ACT.

some control over the quality they sell. Moreover, as discussed in section 5.2, we do not find any robust evidence of selective exit across treatment and control groups, and the treatment effects are, if anything, larger when using the subsample of villages with no change in market structure (Table A.3, columns 3-4).

Could the quality effects be driven solely by the fact that the NGO entered at a price below the prevailing market price, regardless of the quality of the goods sold by the NGO? While we are unaware of any models on experience goods that predict that below-market price entry lead to higher quality, it is plausible that the lower price, by increasing the quantity of ACTs, sped up learning about quality than would otherwise have been the case. Thus, while higher quality itself is likely not due to the price effect, the speed at which this effect come about might be.[48]

Finally, our results obviously do not speak to the question of whether improved quality or lower prices by an existing drug shop (i.e., holding the degree of competition constant) would affect quality. To assess this hypothesis, one would need to conduct a different intervention than the one we evaluate. We also cannot rule out the effect of competition *per se*, for example that the entry effects would have been similar if the NGO sold drugs of the same (low) quality as the market. The observational data presented in Table 1 show there is no indication that villages with higher competition have a lower prevalence of fake drugs, indicating that more shops in a village is no guarantor of high quality. What our results show, however, is that entry by an NGO that is committed to high quality, selling drugs that are priced competitively, decreases the prevalence of fake drugs in competing drug shops, and that this effect appears to be weaker when consumers are less able to infer quality.

6 Conclusion

Information about how the market for medicines works is essential to the evaluation of many of the new initiatives that have been proposed to address the problem of fake drugs in developing countries. With few exceptions, the starting point for these initiatives is the lack of enforcement of regulations to safe-guard public health; i.e. there is little control of the quality, safety and efficacy of the medicines circulating in the market. However, while strengthening the regulatory framework or increased monitoring might be the first-best solution, such reforms are not easily implemented in the short run in countries with weak institutions (alternatively, they would be very costly).

Our findings point to several complementary approaches. First, our results suggest that there is demand, and a market, for providing high-quality drugs. Specifically, although the learning

[48]The data also show that the effects on quality were similar across areas where the initial price difference between the NGO and the local price at baseline varied (appendix Table A.10), suggesting that the quality results are not driven by entry price differences

environment, even for consumers with accurate knowledge of the causes of malaria, is noisy, not least because most consumers lack access to diagnostic testing, we find evidence that consumers can learn about quality over time. This is an important result, because unless consumers have some ability to learn about quality, there are few incentives to build up and maintain a reputation in a weakly regulated and monitored market. These incentives may not be strong enough for the small and independent drug stores that currently dominate the market, as their expected future flow of profits are small and the cost of exit is low. This suggests that policies to facilitate the entry of a larger firm, or a market chain, that can tap into consumers' ability to learn about and pay for quality may be an option to improve drug quality even when firms are not intrinsically motivated to sell high quality. Larger firms can also exploit a number of strategies to strengthen the return to building a good reputation, including branding, advertising, and employing potential signals of quality such as warranties or certification schemes.

The NGO intervention we exploit in the paper is an example of going to scale. At present, the program is not only active in more than 100 local markets in Uganda, but is in the process of expanding. It is too early to tell if their business model is financially viable over the long run. In this paper, we provide evidence of an important externality, as the intervention not only had a direct effect on the supply of authentic antimalarial drugs through the NGO saleswomen, but also changed the market equilibrium. Thus, even if the NGO's private returns are negative, the social returns may be positive.

Our results, however, also indicate that there are limitations to this approach. A key finding is the importance of beliefs, and specifically the implications of the widespread misconceptions about malaria. The evidence suggests that these misperceptions lead to biased reputations for firms, which they in turn seemingly exploit. The experimental results also suggest that when sufficiently many households share these beliefs, the quality improvement caused by the market entry of an outlet committed to high quality is limited. Thus, an implication of our findings is that health education addressing lack of knowledge about diseases may not only induce more appropriate treatment behavior, but may also raise drug quality on the market through households' ability to infer quality.

Our findings also suggest avenues for future research. For example, that mosquitos act as malaria vector has been known since the late 19th century. But misconceptions about the causes of malaria are still common and persistent. Why? Our findings also point to complementarities between the use of new diagnostic technologies such as rapid diagnostic tests for malaria and market quality. Better access to diagnostic tests would not only reduce over-treatment of malaria, but also improve consumers ability to learn about quality and thus raise the incentives to supply high-quality drugs. Finally, 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 can not only directly affect productivity, but also people's willingness to experiment and adopt new technologies.

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Figure 1. Two drug samples

Note: The figure shows two samples of ACT drugs from the drug quality sample. 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

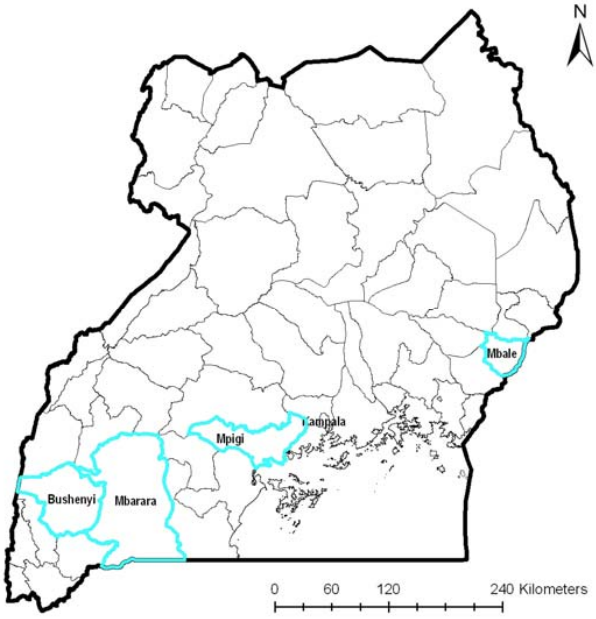
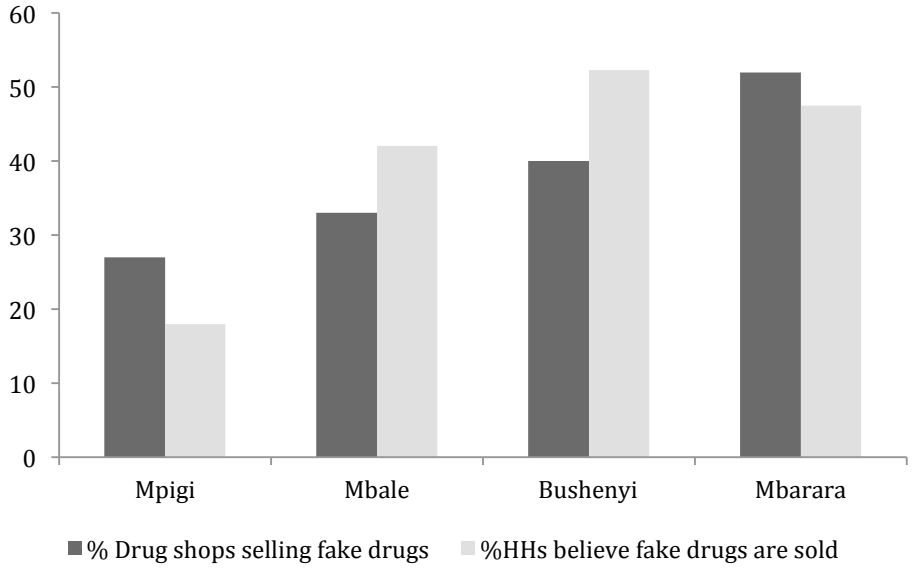


Figure 3. Actual quality and beliefs about quality across districts



Note: Data from the control villages, collapsed at the district level.

Table 1. Prevalence of Fake Antimalarial Drugs

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

Notes: Data from the control villages with drug shops selling ACT at the time of the drug quality survey. One adult dose was purchased by covert shoppers from each shop. For each shop sample, six pills were tested for authenticity using Raman Spectroscopy. A fake drug means that the pill failed the Raman test. In column 1 the number of observations N refers to the number of drug shops, and in columns 2-3 it refers to the number of tested pills. Column 2 reports the unconditional mean in the sample and column 3 reports the mean conditional on the shops selling fake drugs. Competition implies that there are more than one drug shop selling ACT in the village.

Table 2. Correlations: Price and Observable Characteristics

	Price		Observable Characteristics	
Dependent Variable:	Log(Price, Ush)		Share of inspectors of packages believing the sample contains fake drugs	
	(1)	(2)	(3)	(4)
Drug shop sells fake drugs, dummy	0.004		0.134	
	(0.056)		(0.126)	
Share of tested drugs that are fake		-0.085		0.084
		(0.069)		(0.118)
Observations	57	57	57	57
R-squared	0.88	0.88	0.61	0.58
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
Village FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	9.0	9.0	0.30	0.30

Notes: Data from control villages with drug shops selling ACT at the time of the drug quality survey. A fake drug means that the tested pill failed the Raman Spectroscopy authenticity test. *Drug shop sells fake drugs* is a dummy variable equal to one if the drug shop sold pills that failed, and zero otherwise, and the *Share of tested drugs that are fake* is the share of the shop's tested pills that failed. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 3. Correlations: Misconceptions, Household Beliefs and Quality in Drug Shops

	Panel A: Household survey							Panel B: Quality in Drug Shops			
Dependent Variable:	Believes child was sick in malaria last month	Treated child for malaria last month	Child had fever and cough last month	Believes nearest drug shop sells fake drugs, likert scale	Believes nearest drug shop sells fake drugs, dummy	Over-pessimistic prediction (Type I error)	Over-optimistic prediction (Type II error)	Drug shop sells fake drugs, dummy		Share of tested drugs that are fake	
	OLS	OLS	OLS	Ord. Logit	OLS	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
HH with malaria misconceptions	0.066***	0.051**	-0.019	-0.543***	-0.077**	-0.043	0.068**				
	(0.022)	(0.023)	(0.027)	(0.182)	(0.031)	(0.027)	(0.026)				
% of HHs with malaria misconceptions								0.792**	1.387***	0.409***	0.863***
								(0.314)	(0.270)	(0.111)	(0.171)
Secondary education	-0.011	-0.008	0.026	-0.252*	-0.050*	-0.016	0.019		0.102		0.644*
	(0.026)	(0.024)	(0.033)	(0.141)	(0.026)	(0.025)	(0.025)		(0.631)		(0.319)
Tertiary education	-0.070	-0.058	-0.046	-0.376	-0.075*	-0.065**	0.032		0.092		-0.262
	(0.062)	(0.063)	(0.056)	(0.243)	(0.040)	(0.029)	(0.033)		(2.074)		(0.936)
Radio ownership	0.037	0.047*	0.001	-0.103	-0.023	-0.013	0.019		1.055*		0.553
	(0.027)	(0.024)	(0.033)	(0.191)	(0.040)	(0.051)	(0.021)		(0.599)		(0.342)
Electricity	-0.040	-0.035	0.021	0.094	0.031	0.044**	0.010		0.063		-0.082
	(0.028)	(0.026)	(0.036)	(0.154)	(0.030)	(0.018)	(0.016)		(0.535)		(0.200)
Muslim HH	0.021	0.019	0.025	-0.094	-0.016	-0.008	0.001		0.704		-0.101
	(0.032)	(0.030)	(0.032)	(0.169)	(0.032)	(0.039)	(0.013)		(0.713)		(0.315)
Number of u5 children in HH	-0.028**	-0.029**	-0.009	-0.064	-0.010	0.013	0.014*		-0.416		-0.349**
	(0.012)	(0.012)	(0.017)	(0.074)	(0.012)	(0.013)	(0.007)		(0.272)		(0.149)
Number of drug shops at baseline									-0.054		-0.030
									(0.039)		(0.020)
Observations	2552	2552	2556	1435	1,435	819	819	57	57	57	57
R-squared	0.079	0.071	0.118	0.123	0.108	0.206	0.681	0.077	0.153	0.054	0.159
Unit of Analysis	HH/Child	HH/Child	HH/Child	HH	HH	HH	HH	Drug shop	Drug shop	Drug shop	Drug shop
Village FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Dep. Var. Mean	0.41	0.39	0.45	0.34	0.27	0.12	0.31	0.37	0.37	0.19	0.19

Notes: *Panel A* uses baseline household survey data from villages with drug shops selling ACT at the time of the drug quality survey. The respondent is the female head of household. In columns 1-3 the unit of analysis is the child and the respondent did not answer "No, none of them". The dependent variable in column 7 is equal to one if the respondent answered "No, none of them" *and* the share of failed pills in the village was above twenty percent, and zero otherwise. The sample in column 6 and 7 excludes treatment villages since drug quality was measured approximately nine months after intervention had begun. *Panel B:* Shop-level data from control villages with shops selling ACT at the time of the drug quality survey. The dependent variable in column 8-9 indicates whether the drug shop sold any pills that failed the tests, and in columns 10-11 it is the share of the pills that failed. The control variables are the village means for same variables used in panel A. Robust standard errors in parentheses, clustered at the village level in all regressions. *** 1% , ** 5% , * 10% significance.

Table 4. Effects of NGO Entry: Quality of ACT in Drug Shops

	All Drug Shops at Baseline		*All Drug Shops Selling ACT*			
Dependent Variable:	Drug shop sells fake drugs, dummy		Drug shop sells fake drugs, dummy		Share of sold drugs that are fake	
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.153**	-0.183**	-0.197**	-0.208**	-0.108*	-0.131***
	(0.072)	(0.074)	(0.094)	(0.096)	(0.056)	(0.048)
Observations	135	135	93	93	93	93
R-squared	0.08	0.13	0.07	0.13	0.09	0.14
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop
Controls	No	Yes	No	Yes	No	Yes
Number of villages	99	99	47	47	47	47
Dep. Var. Mean in Control	0.26	0.26	0.37	0.37	0.19	0.19

Note: The unit of observation is the drug shop. In columns 1-2 the sample is all shops identified during the baseline shop census, and in columns 3-6 the 93 shops that were open and sold ACT at the time of the quality survey (post-treatment). The dependent variable is equal to one if the drug shop sold fake drugs during the quality survey, and zero otherwise (including whether the shop did not sell ACT). The dependent variables are: in columns 3-4, the same as in columns 1-2; in columns 5-6, the share of the tested pills from the drug shop that failed the Raman Spectroscopy authenticity test; in columns 7-10, the price charged for the full adult dose purchased during the quality survey. *NGO entry* is a dummy variable equal to one if there is a door-to-door NGO distributor selling ACT drugs in the village, and zero otherwise. The control variables are same as in the drug shop regressions in table 3, i.e. the baseline survey village means of: households with secondary education, tertiary education, radio, electricity, muslim denomination; and number of drug shops. All regressions include district fixed effects. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 5. Effects of NGO Entry: Changes in Expectations of Quality

	Dependent Variable: Believes nearest drug shop sells fake drugs						
	Dummy	Dummy	Likert Scale	Dummy	Dummy	Likert Scale	Dummy
	OLS	OLS	Ord. Logit	OLS	OLS	Ord. Logit	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NGO entry*Post-survey	-0.112**	-0.117**	-0.543**	-0.127***	-0.128***	-0.595***	-0.146**
	(0.051)	(0.051)	(0.231)	(0.042)	(0.042)	(0.202)	(0.069)
Post-survey	0.081**	0.079**	0.332*	0.069**	0.068**	0.240	0.057
	(0.037)	(0.037)	(0.186)	(0.033)	(0.033)	(0.186)	(0.039)
NGO entry	0.019	0.011	0.115	0.025	0.019	0.107	0.042
	(0.031)	(0.028)	(0.154)	(0.030)	(0.029)	(0.153)	(0.067)
Observations	2397	2397	2397	2019	2019	2019	1164
R-squared	0.04	0.04	0.02	0.03	0.04	0.03	0.02
Unit of Analysis	HH	HH	HH	HH	HH	HH	HH
Controls	No	Yes	Yes	No	Yes	Yes	Yes
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops post-treatment	Shops post-treatment	Shops post-treatment	Shops post-treatment, only post-surveyed
Number of villages	57	57	57	47	47	47	23
Dep. Var. Mean in control at baseline	0.27	0.27	0.34	0.27	0.27	0.34	0.32

Note: The unit of observation is the household. The samples use survey data from baseline and endline, where the included villages are: in columns 1-3, all the villages with drug shops at baseline; in columns 4-6, villages with drug shops that sold ACT during the quality survey; in column 6, villages with drug shops at baseline and had a post-survey; in column 7 villages with drug shops that sold ACT during the quality survey and were survey both at baseline and endline. The dependent variables use the same definitions as in table 3, and include the same control variables (except for education, which was not collected in the endline survey). All regressions include district fixed effects. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.

Table 6. Heterogeneous Entry Effects on Quality: Misconceptions about Malaria

Dependent Variable:	Drug shop sells fake drugs, dummy			Share of sold drugs that are fake		
	(1)	(2)	(3)	(4)	(5)	(6)
% of HHs with malaria misconceptions * NGO entry	1.72**	1.87***	1.87*	1.19*	1.44***	1.65**
	(0.73)	(0.60)	(0.98)	(0.70)	(0.51)	(0.76)
NGO entry	-0.71***	-0.77***	-0.34	-0.48**	-0.57***	0.35
	(0.26)	(0.24)	(1.50)	(0.23)	(0.18)	(0.75)
% of HHs with malaria misconceptions	0.90**	1.18***	1.45***	0.46***	0.82***	0.91***
	(0.37)	(0.29)	(0.35)	(0.16)	(0.16)	(0.21)
% of HH with secondary education * NGO entry			-1.58			-0.50
			(1.30)			(0.61)
% of HH with tertiary education * NGO entry			-1.56			0.10
			(2.74)			(1.22)
% of HH with radio * NGO entry			-1.52			-1.29**
			(0.98)			(0.59)
% of HH with electricity * NGO entry			0.52			0.09
			(0.82)			(0.34)
% of HH with Muslim denomination * NGO entry			-0.39			-0.12
			(0.93)			(0.42)
Mean number of u5 children per HH * NGO entry			0.88			0.17
			(0.59)			(0.24)
Observations	93	93	93	93	93	93
R-squared	0.16	0.22	0.27	0.16	0.27	0.29
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop
Controls	No	Yes	Yes	No	Yes	Yes
Number of villages	47	47	47	47	47	47
Dep. Var. Mean in Control Villages	0.37	0.37	0.37	0.19	0.19	0.19

Note: The sample consists of drug shops selling ACT during the quality survey. The dependent variables: in columns 1-3, a dummy equal to one if the drug shop sold fake drugs during the quality survey, and zero otherwise; in columns 4-6, the share of the tested pills from the drug shop that failed the Raman Spectroscopy authenticity test. % of HHs with malaria misconceptions has the same definition as in table 3, using data from the baseline survey. The control variables are the same as in table 4. All regressions include district fixed effects. Robust standard errors in parenthesis, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 7. Effects of NGO Entry: Price

	Drug shop data: All shops selling ACT			
Dependent Variable:	Log(Price, Ush)		Price, '000 Ush	
	(1)	(2)	(3)	(4)
NGO entry	-0.146**	-0.198***	-1.45**	-1.92***
	(0.058)	(0.051)	(0.56)	(0.43)
Observations	93	93	93	93
R-squared	0.53	0.65	0.52	0.65
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
Controls	No	Yes	No	Yes
Number of villages	47	47	47	47
Dep. Var. Mean in Control	9.0	9.0	8.9	8.9

Note: The sample and control variables are the same as in table 4. The dependent variable is the price for a full dose of ACT, from the covert shopper data. All regressions include district fixed effects. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 8. Effects of NGO Entry: Quantity

	Treatment of children reported sick in malaria								
Dependent variable:	Child Treated with ACT, dummy			# ACT pills, any source			# ACT pills, sourced from drug shops		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NGO entry*Post-survey	-0.05	-0.04	-0.07	2.45**	2.52**	3.39**	0.40	0.08	0.53
	(0.07)	(0.09)	(0.10)	(0.94)	(1.16)	(1.56)	(0.82)	(0.84)	(1.22)
Post-survey	0.33***	0.32***	0.33***	-0.18	-0.08	-0.47	-0.73	-0.86	-0.23
	(0.04)	(0.05)	(0.04)	(0.49)	(0.55)	(0.67)	(0.58)	(0.52)	(0.68)
NGO entry	0.05	0.04	0.08	-0.39	-0.69*	-1.24*	0.16	0.23	-0.65
	(0.04)	(0.05)	(0.06)	-0.53	(0.36)	(0.72)	(0.48)	(0.49)	(1.19)
Observations	1586	1321	704	619	513	301	619	513	301
R-squared	0.08	0.08	0.13	0.04	0.10	0.11	0.11	0.13	0.13
Unit of Analysis	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample of villages	Shops at baseline	Shops post-treatment	Shops post-treat., only post-surveyed	Shops at baseline	Shops post-treatment	Shops post-treat., only post-surveyed	Shops at baseline	Shops post-treatment	Shops post-treat., only post-surveyed
Number of villages	54	45	23	54	45	23	54	45	23
Dep. Var. Mean at baseline	0.37	0.37	0.33	6.77	6.66	6.71	3.85	4.06	2.80

Note: The sample consists of children reported sick in malaria in the last month. The dependent variables are: in columns 1-3, a dummy indicating whether the child was treated with ACT, and zero if treated with non-ACT antimalarial; in columns 4-6, the number of pills that were acquired for treatment from any source, conditional on treatment with ACT; in columns 7-9, the number of pills from private drug shops that were acquired for treatment, conditional on treatment with ACT. The control variables are the same as in table 5. All regressions include district fixed effects. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.

Appendix

Proof of proposition 1: Let $\Pi\left(m;\tilde{m}^H,\tilde{m}^O\right)$ denote expected profit given expectations $\tilde{m}^H$ and $\tilde{m}^O$. Suppose $\tilde{m}^H = 1$ and $\tilde{m}^O = \frac{\theta_L}{\theta_H}$. Then $p_1 = \bar{\theta}\left(\phi\tilde{m}^H + (1-\phi)\tilde{m}^O\right) = \bar{\theta}\left(\phi + (1-\phi)\frac{\theta_L}{\theta_H}\right)$. If the seller sets $m = m^*$, $(\sigma_1 - \omega) = \theta_L$ with probability $1-\pi$. The posterior belief that the seller is honest is $\phi_{\theta_L} = \frac{\pi\phi}{\pi\phi+(1-\pi)(1-\phi)}$, and the seller's expected revenue in period 2 is $p_2 = \bar{\theta}\phi_{\theta_L}$. Condition (i) ensures that the seller's expected profit $\Pi\left(\frac{\theta_L}{\theta_H};1,\frac{\theta_L}{\theta_H}\right) > 0$. Conditions (i) and (ii) ensure that no deviation from choosing m^* is profitable; i.e., $\Pi\left(\frac{\theta_L}{\theta_H};1,\frac{\theta_L}{\theta_H}\right) > \Pi\left(0;1,\frac{\theta_L}{\theta_H}\right)$ and $\Pi\left(\frac{\theta_L}{\theta_H};1,\frac{\theta_L}{\theta_H}\right) > \Pi\left(1;1,\frac{\theta_L}{\theta_H}\right)$. Condition (ii) also ensures that the equilibrium is a unique pure strategy equilibrium; i.e., $\Pi(1;1,1) < \Pi\left(\frac{\theta_L}{\theta_H};1,1\right)$. Note finally that $\Pi(1;1,1) > \Pi\left(\frac{\theta_L}{\theta_H};1,\frac{\theta_L}{\theta_H}\right)$ by condition (ii). That is, the opportunistic seller would prefer to commit to set $m = 1$ (in period 1).

Proof of proposition 2: Following the steps above, if conditions (i) and (ii) hold, no deviation from choosing m^{**} is profitable and the equilibrium is a unique pure strategy equilibrium.

Proof of proposition 3: Suppose $\tilde{m}_I^O = \tilde{m}_{NGO}^O = 1$ and $\tilde{m}_I^H = \tilde{m}_{NGO}^H = 1$. Then both sellers will be perceived as identical and the posterior belief that the incumbent [NGO] is honest is $\phi_\sigma = \phi$ and $p_t = \bar{\theta}\phi$. Each seller serves half of the customer base. As $c = \bar{\theta}\phi$, no deviation from choosing m_I^* is profitable, ensuring we have a unique pure strategy equilibrium.

Proof of proposition 4: Suppose $\tilde{m}_I^O = \tilde{m}_{NGO}^O = 1$ and $\tilde{m}_I^H = \tilde{m}_{NGO}^H = 1$, and let ϕ_σ^S denote the posterior probability that seller S is honest. If the sellers set $m_I^{**} = (\theta_H - \omega)/\theta_H$ and $m_{NGO} = 1, \sigma_I = \theta_H$ and $\sigma_{NGO} = \theta_H + \omega$ in a high malaria state and $\sigma_I = \theta_L + \omega\left(1 - \frac{\theta_L}{\theta_M}\right)$ and $\sigma_{NGO} = \theta_L + \omega$ in a low malaria state. Thus, $\phi_\sigma^I = \phi_\sigma^{NGO}$ for each malaria realization. Each seller serves half of the customer base, and as $c = \bar{\theta}\phi$, no deviation from choosing m_I^{**} is profitable.

Appendix Table A.1. Baseline Characteristics

	Panel A: All Villages					*Panel B: Villages with Drug Shops at Baseline*				
	Obs.	Mean, Treatment	Mean, Control	Diff.	P-value	Obs.	Mean, Treatment	Mean, Control	Diff.	P-value
Household Characteristics										
Male head of HH has secondary education, dummy	2 980	0.30	0.27	0.03	0.32	1 817	0.32	0.29	0.03	0.47
Male head of HH has tertiary education, dummy	2 980	0.05	0.05	0.00	0.74	1 817	0.07	0.05	0.03	0.06*
Radio ownership, dummy	2 980	0.82	0.79	0.04	0.17	1 817	0.85	0.82	0.03	0.33
Electricity, dummy	2 980	0.19	0.16	0.03	0.52	1 817	0.26	0.19	0.06	0.30
Thatched roof, dummy	2 967	0.03	0.04	-0.01	0.36	1 810	0.02	0.04	-0.02	0.15
Muslim HH, dummy	2 980	0.19	0.17	0.02	0.46	1 817	0.19	0.19	0.00	0.94
Number of u5 children in HH	2 980	1.72	1.75	-0.03	0.57	1 817	1.68	1.73	-0.05	0.41
Child reported sick in malaria in the last month, dummy	5 159	0.43	0.41	0.03	0.32	3 087	0.44	0.39	0.05	0.14
Sick child was treated with ACT, dummy	2 169	0.41	0.37	0.04	0.26	1 263	0.40	0.35	0.05	0.31
The ACT was bought in a drug shop, dummy	749	0.60	0.58	0.01	0.84	415	0.64	0.54	0.10	0.24
# ACT pills for treating sick child, any source	751	6.49	6.69	-0.21	0.52	415	6.67	6.87	-0.21	0.68
Has heard of ACT, dummy	2 980	0.95	0.95	0.00	0.99	1,817	0.95	0.95	0.00	0.98
Believes ACT is highly effective, dummy	2 728	0.90	0.90	0.01	0.73	1 670	0.91	0.89	0.03	0.15
Believes non-ACT drugs are highly effective, dummy	2 930	0.83	0.86	-0.04	0.26	1,785	0.86	0.85	0.01	0.88
Believes nearest drug shop sells fake drugs, dummy	2 841	0.28	0.26	0.03	0.42	1723	0.29	0.26	0.04	0.43
HH with malaria misconceptions, dummy	2 980	0.32	0.36	-0.04	0.16	1 817	0.32	0.37	-0.04	0.17
Village Characteristics										
Number of households in the village	99	192.8	190.8	1.98	0.96	57	197.6	208.4	-10.7	0.84
Number of drug shops in the village	99	1.12	1.60	-0.48	0.20	57	2.12	2.58	-0.47	0.36
Village has at least one drug shop	99	0.53	0.62	-0.09	0.37	57	1.00	1.00	0.00	N/A
Village is a local monopoly (one drug shop)	99	0.27	0.26	0.01	0.95	57	0.50	0.42	0.08	0.55

Note: There are 99 study villages in the full sample (of which 49 are treatment villages) and 57 villages with drug shops at baseline (of which 26 are treatment villages). Treatment is a door-to-door NGO saleswoman selling authentic ACT drugs in the village. P-values for household characteristics are calculated using village-clustered standard errors, and robust standard errors are used for village characteristics. *** 1%, ** 5% , * 10% significance.

Appendix Table A.2. Baseline Characteristics: Attrition Check

	Panel A: Villages with Drug Shops at Baseline					*Panel B: Villages with Drug Shops at Baseline and Endline*				
	Obs.	Mean, Has Drug Shop at Endline	Mean, No Drug Shop at Endline	Diff.	P-value	Obs.	Mean, Treatment	Mean, Control	Diff.	P-value
Household Characteristics at Baseline										
Male head of HH has secondary education, dummy	1 817	0.30	0.29	0.02	0.68	1 510	0.32	0.29	0.03	0.55
Male head of HH has tertiary education, dummy	1 817	0.06	0.06	0.01	0.72	1 510	0.07	0.05	0.02	0.16
Radio ownership, dummy	1 817	0.84	0.79	0.04	0.21	1 510	0.84	0.83	0.01	0.71
Electricity, dummy	1 817	0.24	0.15	0.08	0.28	1 510	0.27	0.21	0.06	0.40
Thatched roof, dummy	1 810	0.03	0.04	-0.01	0.36	1 505	0.02	0.04	-0.01	0.30
Muslim HH, dummy	1 817	0.19	0.21	-0.03	0.65	1 510	0.17	0.20	-0.02	0.62
Number of u5 children in HH	1 817	1.70	1.75	-0.05	0.60	1 510	1.68	1.70	-0.02	0.72
Child reported sick in malaria in the last month, dummy	3 087	0.41	0.41	-0.01	0.86	2 552	0.45	0.38	0.07	0.06
Sick child was treated with ACT, dummy	1 263	0.37	0.41	-0.04	0.51	1 041	0.39	0.35	0.04	0.49
The ACT was bought in a drug shop, dummy	415	0.62	0.48	0.14	0.19	336	0.66	0.57	0.10	0.28
# ACT pills for treating the sick child	415	6.66	7.23	-0.57	0.59	336	6.42	6.89	-0.47	0.24
Has heard of ACT, dummy	1 817	0.95	0.95	0.00	0.97	1 510	0.96	0.95	0.01	0.50
Believes ACT is highly effective, dummy	1 670	0.89	0.92	-0.03	0.12	1 385	0.90	0.89	0.02	0.40
Believes non-ACT drugs are highly effective, dummy	1 785	0.85	0.90	-0.06	0.10	1 482	0.84	0.85	-0.01	0.90
Believes nearest drug shop sells fake drugs, dummy	1 723	0.27	0.30	-0.03	0.72	1 435	0.29	0.26	0.04	0.41
HH with malaria misconceptions, dummy	1 817	0.35	0.32	0.04	0.26	1 510	0.33	0.38	-0.049	0.18
Village Characteristics at Baseline										
Number of households in the village	57	188.4	274.4	-86.0	0.39	47	185.1	190.8	-5.77	0.90
Number of drug shops in the village	57	2.66	1.00	1.66	0.00***	47	2.65	2.74	-0.09	0.88
Village is local monopoly (one drug shop)	57	0.34	1.00	-0.66	0.00***	47	0.35	0.33	0.02	0.91
Treatment village	57	0.43	0.60	-0.17	0.32	47	1.00	0.00	1.00	N/A

Note: There are 57 (47) villages with at least one drug shop at baseline (endline), of which 26 (20) are treatment. Treatment is a door-to-door NGO distributor selling authentic ACT drugs in the village. P-values for household characteristics are calculated using village-clustered standard errors, and robust standard errors are used for village characteristics. ** 5% , * 10% significance.

Appendix Table A.3. Village-Level Estimates and Exit Tests

	Sample: Villages with and without shops at baseline		Sample: Drug shops in villages with no change in the number of shops		Sample: All drug shops from baseline	
Dependent Variable:	# of drug shops selling fake drugs in the village	Drug shop sells fake drugs, dummy	Drug shop sells fake drugs, dummy	Share of sold drugs that are fake	Exit	Conditional exit
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.263**	-0.129*	-0.260*	-0.098	-0.029	0.076
	(0.118)	(0.072)	(0.140)	(0.078)	(0.044)	(0.082)
Observations	99	99	48	48	135	135
R-squared	0.23	0.22	0.07	0.08	0.04	0.06
Unit of Analysis	Village	Village	Drug shop	Drug Shop	Drug shop	Drug shop
Controls	No	No	No	No	No	No
Dep. Var. Mean, Control Vil.	0.42	0.26	0.47	0.25	0.11	0.29

Note: Village level data in columns 1-2 from all villages, including those with no drug shops at baseline. The dependent variable in column 1 is the number of shop that sell fake ACT in the drug quality survey. If there are no shops in the village, it is equal to zero. In column 2 the outcome variable is a dummy if there is at least one drug shop that sells fake drugs in the village, and zero otherwise (i.e., including if there are no shops). Outlet level data in columns 3-4 from the subsample of drug shops in villages with no change in market structure between baseline and the time of the drug quality survey. The dependent variable in column 3 is a dummy indicating whether the drug shop sold pills that failed the tests, and in column 4 it is the share of the drug shop's pills that failed. Data in columns 5-6 is from the 135 drug shops identified at baseline. The dependent variable in column 5 is an indicator variable taking the value one if the outlet was identified at baseline but was not open for business at the time of the drug quality survey. The dependent variable in column 6 is an indicator variable taking the value 1 if the outlet was identified at baseline but did not sell ACT at the time of the drug quality survey. *NGO entry* is a dummy variable equal to one if there is a door-to-door saleswoman selling authentic ACT drugs in the village, and zero otherwise. Robust standard errors, clustered at the village level in columns 5-6. *** 1% , ** 5% , * 10% significance.

Appendix Table A.4. Beliefs about Antimalarial Drug Quality

		HH believes nearest drug shop in village sells fake drugs?	
		No	Yes
Drug shops in village sell fake drugs?	No	40.2% [43.8%]	12.5% [14.9%]
	Yes	34.3% [30.6%]	13.1% [10.6%]
	Total	74.5%	25.5%

Note. Baseline household survey data from control villages with drug shops selling ACT. "Drug shops in village sell fake drugs?" equals Yes if drugs from the village failed the autheniticity tests (in brackets: at least 20 percent failed]. Household beliefs equal No if the answer to the question: "Do you expect that the antimalarial medicines sold by the nearest drug shop are fake?" is "No, none of them", and Yes otherwise. The total number of observations in 819.

Appendix Table A.5. Correlations: Misconceptions and Beliefs, Excluding Controls

Dependent Variable:	Believes ACT is highly effective	Believes non-ACT drugs are highly effective	Believes child was sick in malaria last month	Treated child for malaria last month	Child had fever and cough last month	Believes nearest drug shop sells fake drugs, likert	Believes nearest drug shop sells fake drugs, dummy	Over-pessimistic prediction (Type I error)	Over-optimistic prediction (Type II error)
	OLS	OLS	OLS	OLS	OLS	Ord. Logit	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
HH with malaria misconceptions	0.035	0.000	0.072***	0.056**	-0.019	0.582***	0.065**	-0.045	0.068**
	(0.022)	(0.028)	(0.022)	(0.022)	(0.028)	(0.105)	(0.026)	(0.028)	(0.026)
Observations	1385	1482	2552	2552	2556	1435	1385	819	819
R-squared	0.06	0.15	0.07	0.07	0.12	0.08	0.05	0.20	0.68
Unit of Analysis	HH	HH	Child	Child	Child	HH	HH	HH	HH
Village FE	Yes	Yes	No	No	No	No	No	No	No
Dep. Var. Mean	0.41	0.39	0.41	0.39	0.45	0.34	0.26	0.12	0.31

Note: The sample and variable definitions are the same as in table 3. Robust standard errors in parentheses, clustered at the village level in all regressions. *** 1% , ** 5% , * 10% significance.

Appendix Table A.6. Correlations: Expectations of Quality and Demand for ACT medicine

	Treatment of children reported sick in malaria					
Dependent Variable:	Treated child with ACT, dummy		The ACT was acquired from a private drug shop, dummy.		# ACT pills, sourced from drug shop	
	(1)	(2)	(3)	(4)	(5)	(6)
Believes drug shop sells fake drugs, dummy	-0.011	-0.007	-0.118*	-0.109*	-1.27**	-1.27**
	(0.050)	(0.050)	(0.069)	(0.063)	(0.55)	(0.54)
Observations	982	982	320	320	320	320
R-squared	0.14	0.15	0.38	0.44	0.21	0.24
Unit of Analysis	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
HH Controls	No	Yes	No	Yes	No	Yes
Dep. Var. Mean	0.37	0.37	0.63	0.63	4.15	4.15

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 of the answer is "No, none of them", and one otherwise. Baseline data from 47 villages with drug shops selling ACT. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Appendix Table A.7. Effects of NGO Entry: Expectations of Quality and Quantity, Post Survey Only

Dependent variable:	Believes nearest drug shop sells fake drugs, dummy		Child treated with ACT, dummy		# ACT pills, any source		# ACT pills, sourced from drug shop	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO entry	-0.070**	-0.081***	0.043	0.029	2.20***	2.45**	-0.131	-0.682
	(0.031)	(0.029)	(0.057)	(0.078)	(0.70)	(0.97)	(0.684)	(0.637)
Observations	672	582	318	275	200	173	200	173
R-squared	0.02	0.03	0.03	0.04	0.13	0.17	0.13	0.21
Unit of Analysis	HH	HH	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample of villages	Shops at baseline	Shops post-treatment	Shops at baseline	Shops post-treatment	Shops at baseline	Shops post-treatment	Shops at baseline	Shops post-treatment
Number of villages	26	23	26	23	26	23	26	23
Dep. Var. Mean in control	0.36	0.34	0.66	0.65	6.66	6.70	2.83	2.93

Note: The sample and variables definitions in column 1-2 are the same as in table 5 and in column 3-8 the same as in table 8, except that the sample is restricted to endline data only. In columns 1-2 the unit of analysis is the household, and in columns 3-8 children reported sick in malaria in the last month. All regressions include district fixed effects. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.

Appendix Table A.8. Heterogeneous Effects on Price: Misconceptions about Malaria

Dependent Variable:	Log(Price, Ush)			Price, '000 Ush		
	(1)	(2)	(3)	(4)	(5)	(6)
% of HHs with malaria misconceptions * NGO entry	-0.12	-0.09	0.37	-3.49	-2.67	-0.34
	(0.59)	(0.55)	(0.84)	(5.26)	(4.49)	(5.88)
NGO entry	-0.11	-0.15	-1.06	-0.34	-0.87	-8.17
	(0.23)	(0.22)	(0.93)	(1.91)	(1.71)	(6.56)
% of HHs with malaria misconceptions	-0.08	0.22	0.35	-1.15	1.48	2.88
	(0.24)	(0.16)	(0.21)	(2.13)	(1.34)	(1.79)
% of HH with secondary education * NGO entry			0.42			2.24
			(0.68)			(4.64)
% of HH with tertiary education * NGO entry			-1.09			-6.69
			(1.11)			(9.45)
% of HH with radio * NGO entry			-0.15			-2.43
			(0.80)			(5.94)
% of HH with electricity * NGO entry			0.27			2.39
			(0.40)			(2.98)
% of HH that are Muslim * NGO entry			-0.65			-7.75**
			(0.44)			(3.70)
Mean number of u5 children in HH * NGO entry			0.55*			5.74**
			(0.28)			(2.31)
Observations	93	93	93	93	93	93
R-squared	0.53	0.66	0.69	0.52	0.66	0.70
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop
Controls	No	Yes	Yes	No	Yes	Yes
Dep. Var. Mean in Control Villages	9.0	9.0	9.0	8.91	8.91	8.91

Note: The sample, dependent variables and controls are the same as in table 7. Robust standard errors in parenthesis, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table A.9. Effects of NGO Entry: Beliefs and Knowledge about Malaria and Medicines

	Misconceptions about Malaria Transmission						Knowledge about Antimalarial Medicines					
Dependent Variable:	HH with malaria misconceptions, dummy		Direct contact with someone that has malaria		Drinking water containing mosquito eggs		Has heard of ACT		Believes ACT is highly effective		Believes non-ACT drugs are highly effective	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NGO entry	-0.01	0.01	0.05	-0.00	-0.01	0.03	-0.02	-0.01	0.01	0.02	-0.00	-0.00
	(0.04)	(0.03)	(0.06)	(0.06)	(0.06)	(0.05)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)
Observations	684	594	639	554	667	577	685	595	651	569	644	559
R-squared	0.04	0.05	0.05	0.04	0.09	0.10	0.04	0.04	0.03	0.05	0.02	0.02
Sample of villages	Shops at baseline	Shops post-treat.	Shops at baseline	Shops post-treat.	Shops at baseline	Shops post-treat.	Shops at baseline	Shops post-treat.	Shops at baseline	Shops post-treat.	Shops at baseline	Shops post-treat.
Unit of Analysis	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean, Control Vil.	0.41	0.41	0.66	0.67	0.56	0.55	0.98	0.98	0.95	0.94	0.84	0.85

Note: Data from the endline household survey conducted in 48 randomly sampled villages, where the samples consist of either the 26 villages that had shops at baseline, and the 23 villages that had shops selling ACT at the time of the drug quality survey (shops post-treatment). *T*he dependent variables are: in columns 1-2, same definition as in table 3; in columns 3-6, they correspond to the individual misconceptions questions, where the dummy is equal to one if the household has false beliefs, and zero if beliefs are correct; in columns 7-9, a dummy indicating if the respondent has heard of ACT; in columns 9-12, a dummy indicating if the respondent answers "highly effective" to the question "How effective do you think that this medicine is in treating malaria today?" (options: highly effective, somewhat effective, not effective). The non-ACT medicines are Chloroquine, Quinine, and SP, and the dummies in columns 11-12 are equal to one if the respondent answers highly effective to at least one of the drugs. The control variables are the same as in table 5. *** 1% , ** 5% , * 10% significance.

Appendix Table A.10. Heterogeneous Entry Effects on Quality and Price by NGO Subsidy

	Quality				Price			
Dependent Variable:	Drug shop sells fake drugs, dummy		Share of drugs that are fake		Price, '000 Ush		Log(Price, Ush)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO entry	-0.208**	-0.275*	-0.131***	-0.186**	-1.916***	-1.119*	-0.198***	-0.137*
	(0.096)	(0.161)	(0.048)	(0.071)	(0.427)	(0.608)	(0.051)	(0.081)
NGO entry * NGO subsidy, '000 Ush		0.027		0.022		-0.322**		-0.025
		(0.042)		(0.021)		(0.137)		(0.017)
Observations	93	93	93	93	93	93	93	93
R-squared	0.13	0.13	0.14	0.15	0.65	0.67	0.65	0.66
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean in Control Villages	0.37	0.37	0.19	0.19	8.91	8.91	9.0	9.0

Note: The sample, outcomes and control variables are the same as in Table 7. *NGO entry* is a dummy variable equal to one if there is a door-to-door NGO distributor selling authentic ACT drugs in the village, and zero otherwise. *NGO subsidy* is the difference between the district mean ACT price in drug shops in control villages and the NGO price, in thousands of Ugandan shillings (mean=2.2, s.d.=2.4). All regressions include district fixed effects. Robust standard errors in parenthesis, clustered at the village level. *** 1% , ** 5% , * 10% significance.