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

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First Draft: Dec 2011, This Version: Feb 2016

Abstract

Retail markets for medicines in developing countries are plagued by counterfeit and substandard products, with recent estimates, for example, suggesting that as much as a third of antimalarial (ACTs) drugs sold are fake. Using data from a randomized controlled trial we investigate how the entry of a retailer selling high quality medicine affects incumbent sellers' behavior. We identify two mechanisms that can improve the market equilibrium: Exit of incumbent drug shops selling poor quality and a shift to higher quality drugs by outlets remaining. We find that the reduced form treatment effects are large: Approximately a year after the new market actor entered the share of incumbent firms selling fake ACTs dropped by more than 50 percent in the intervention compared to the control group. Imposing structure derived from the model and jointly estimate the exit and intensive margin effects, we find that the intensive margin effect accounts for 50-70% of the total effect, and the exit effect accounting for the remaining 30-50%.

*Earlier versions of this paper have been circulated under two different titles, including "The Market for (Fake) Antimalarial Medicine: Evidence from Uganda". We are grateful for comments and suggestions by Philippe Aghion, Tessa Bold, Raquel Fernandez, Asim Khwaja, Michael Kremer, Nancy Qian, and Richard Zeckhauser, as well as seminar participants at Harvard/MIT, IIES Stockholm U, LSE, NHH, NYU, UPF, Yale SPH, Yale Economics Dept., Tufts U, the CEPR-Development 2012, EEA 2012, and AEA 2013 conferences. We would also like to thank Annalise Blum, Aletheia Donald, Deanna Ford, Sarah McCune and Charles Ntale for excellent research assistance and management, and CIFF, Living Goods and BRAC for their collaboration. All mistakes are our own. Financial support from the Swedish Research Council (421-2009-2209), the Program for Development Research, SIDA; J-PAL, the William F. Milton Fund at Harvard Medical School; and Harvard Center for Population and Development Studies is gratefully acknowledged.

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1 Introduction

Malaria continues to be one of the major killer-diseases in Africa, despite existence of effective prevention methods (like insecticide-treated bed nets, ITNs) and effective curative treatments (early treatment with artemisinin-based combination therapy, ACT).[1] While the reason for this public health failure is likely to be multifaceted, recent evidence from retail markets for ACT drugs suggest that poor quality of the medicine is one important factor.[2]

Antimalarial medicine is an experience good; i.e., consumers observe neither the quality of the medicine sold nor the utility it will yield before purchase. Learning about quality thus has to be based on health experience after purchase and treatment. However, because malaria mimics several other diseases both in initial symptoms and in signs of severe illness, and because symptomatic diagnosis (whether the individual has fever or not) rather than parasite-based diagnostic testing is the norm in most of Africa, misdiagnosis is common.[3] Misdiagnosis, in turn, is likely to hamper learning about both the effectiveness of ACTs and their quality (Adhvaryu, 2014).

Can the entry of a retailer selling high quality medicine affect the market equilibrium in such an environment and if so how? We use data from a randomized controlled trial, embedded within the scale-up of a new health delivery program in Uganda, to investigate this question.

We start by presenting a simple experience good model. In markets for such goods a firm's incentive to provide high-quality goods crucially hinges on consumers' ability to learn about quality (Shapiro, 1982; Mailath and Samuelson, 2001). We show that the entry of a retailer committed to sell high quality provides consumers with additional information and affects the market equilibrium in two ways: (i) exit of the retailers selling the lowest quality; and (ii) increased quality of drugs sold by the remaining retailers.

To assess these predictions, we exploit data from the first phase of a randomized controlled field trial in which the entry of a new market actor, acting as the sales agent for

[1] In Africa alone there were 174 million cases of malaria in 2010, and an estimated 596 000 to over 1 million deaths. Children under the age of five account for the majority of the deaths (WHO, 2011a; Murray et al., 2012).

[2] 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).

[3] 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. (2015) show that only 38 percent of adults who seek treatment for malaria at drug shops in Kenya actually have malaria.

two NGOs by selling authentic ACT drugs below local market prices, was randomly assigned across local markets (villages). To our knowledge, this is the first study to use a randomized intervention to investigate the determinants of drug quality in developing countries.[4] We start by estimating the reduced form effects of competition from a high quality seller on the quality of drugs sold by incumbent sellers, with quality of antimalarial medicine measured using Raman Spectroscopy. Approximately nine months after the new market actor entered, the share of firms selling fake ACTs dropped by more than 50 percent in the intervention compared to the comparison group.[5] Imposing structure derived from the model and jointly estimate the exit and intensive margin effects, we further show that the intensive margin effect accounts for 50-70% of the total effect, while the exit effect accounts for the remaining 30-50%.

In the model, incumbent sellers change behavior because consumers' ability to learn about the quality of the drugs sold by the incumbent improves following the entry of the new seller. We provide evidence, using household survey data, that this mechanism is indeed at play. At baseline, households in the two assignment arms were as likely to report that the incumbent shops sell fake antimalarial pills. Consistent with the reduction in low quality ACT drugs, and learning, however, a year into the intervention we show that households in intervention villages were significantly less likely to believe that incumbent shops sell fake antimalarials as compared to control villages. The entry of the new market actor also resulted in lower market prices for ACTs, consistent with the existence of significant ex ante mark-ups in the retail market, and an overall increase in demand.

These results have clear policy implications. A wide variety of regulatory policies have recently been put forward to address the problem of fake drugs. 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 (see e.g. *Lancet*, 2012). However, while strengthening the regulatory framework or increasing 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.

[4] A related paper by Bennett and Yin (2015) uses a difference-in-difference strategy to investigate the impact of chain store entry on the quality of antibiotics in Hyderabad, India. Their results echo some of our findings on quality and price, at least from a qualitative perspective, but in a different market where drug quality appears to be higher.

[5] Poor quality drugs are counterfeit or falsified drugs where there has been a deliberate and fraudulent mislabeling of the medicine with respect to identity and/or source, and with usually no or wrong active pharmaceutical ingredients, or of sub-standard quality (where poor practices on behalf of the authorized manufacturer result in inadequate content). We use the term fake drugs for drugs that fail chemical analyses using Raman spectroscopy (see section 4).

First, we find that consumers can identify quality improvements in the market although the learning environment is noisy, suggesting that seller do have pecuniary incentives to build up and maintain a high quality reputation in the weakly regulated and unmonitored markets we study. While these incentives may not be strong enough for the small and informal drug stores that currently dominate the market, our findings suggest 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.[6]

Second, the NGO intervention we exploit in the paper is in itself a promising approach. Their franchised direct selling (business-in-a-bag) business is currently active in close to 1000 villages with a total population of 1.4 million and the scale-up is continuing. A recently completed impact evaluation of their business program also shows promising effects, including a 27% reduction in under-five mortality (Björkman-Nyqvist, Guariso, Svensson, and Yanagizawa-Drott, 2015). While the NGO intervention likely had an impact on child health through a variety of channels, the direct effect through the supply of authentic ACTs, and the indirect effect through the changed market equilibrium for ACT drugs, are likely to be contributing factors.

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.

2 The Market for Antimalarial Drugs

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. Children under the age of five account for the majority of the deaths (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

[6]Larger firms can also exploit a number of strategies to strengthen the return to building a good reputation, including branding and advertising.

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.

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. 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 high quality drugs (Harris et al., 2009). Poor quality ACTs can also have long-run adverse effects on both children and adults.[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. (2015) show that only 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

[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.

[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., 2015). Fourth, compliance with test results, both by individuals and health practitioners, is weak (Juma and Zurovac, 2011).

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, 2014).

In most of Africa, and, in particular, in rural areas and among poorer households, treatment of malaria is largely done at home using 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]

2.2 Supply

Compared to older, synthetic forms of malaria medicine, artemisinin is significantly more expensive to produce and thus a prime suspect for counterfeiting. High costs of production might also imply stronger incentives for producers to use less stringent production processes, with substandard quality as a result. 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

[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.

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

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

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 The market for fake drugs

In this section we provide a simple two-period model to help shed light on incumbent sellers' behavior in response to the entry of a seller committed to selling high quality drugs.[12]

3.1 A simple model

Consider a market with a continuum of identical consumers of unit mass. There are two periods. Initially there is one seller on the market.

In each period, consumers contracts fever that may either be due to malaria or some other disease. Consumers do not know the exact cause of their fever and lacking ability to diagnose the cause, we assume each consumer is willing to pay a price p, normalized to 1, for treatment of antimalarial drugs.[13]

The likelihood of recovering from treatment with antimalarial drugs depends on two unknown (for the consumer) factors: whether she suffers from malaria and whether the antimalarial drug is authentic (high quality). Clearly people observe their own outcome after taking the drug but that statistic, given that the cause of their fever is unknown, does not reveal the overall quality in the market place. Therefore, we assume individuals base their decisions on a noisy (common) signal, s, of the amount of fake drugs in their market, where $s = d + z$ and where d is the share of fake drugs being sold and z has a distribution function F with density f. Note that s should not be interpreted as the share of bad drugs

[12]The model draws on Mailath and Samuelson (2001) and Acemoglu et al. (2013).

[13]The willingness to pay a price p effectively assumes away the sellers' pricing decision. We thus focus attention on the quality choice. As discussed below prices do not seem to vary systematically with quality and in any case our result would hold if we, for example, specified a utility function and assume that each consumer pays her expected utility amount for the antimalarial medicine.

in circulation (as $s \in \mathbb{R}$) but rather a signal on how common this is.[14]

The drug store sets the share of fake drugs in period 1, d_1, to maximize expected discounted profit, given by $\Pi_1(d_1) + \delta P(d_1)\Pi_2(d_2)$, where $\Pi_t(d_t) = 1 - C(d_t)$ is revenues minus costs in period t, δ denotes the discount factor, with $0 < \delta < 1$, and $P(d_1)$ is the probability that the incumbent seller remains in the market in period 2 conditional on the seller's choice of fake drugs to sell in period 1. The cost of selling a share d_t of fake drugs is given by $C(d_t) = c(1 - d_t) + d_t\mu + \frac{1}{2}d_t^2$, with $0 < c < 1$. The first term in the cost function captures the fact that authentic drugs are more expensive, with c being the marginal cost. The second term captures the moral cost, denoted by μ, of selling fake drugs to sick patients, and the third term captures the risk of getting caught if selling fake drugs, with the risk increasing in the share of fake drugs sold (the last two terms are expressed in monetary terms).[15]

Firm owners differ in their moral cost μ of selling fake drugs. To simplify, assume there are two types: High moral cost types, with $\mu \geq c$, and low moral cost types, with $\mu < c$. We label the high moral cost types as "honest" (H) and the low moral cost types as "opportunistic" (O), with superscript $T = \{H, O\}$ denoting type. Note that an honest type, by assumption, always will always set $d = 0$ (because the moral cost of selling fake drugs is too high) while an opportunistic type might set a $d > 0$. Nature draws the type at the start of period 1, with the honest type chosen with probability θ. As the honest type always sets $d = 0$, our focus is on the opportunistic type.

Consumers can either buy antimalarial medicine from the store in their villages or they can travel to a (nearby) village and buy the drug. Consumers do not receive a signal about the overall quality in the nearby market, but know that the likelihood that the seller in the nearby market is honest is θ.

The timing of events is as follows:

1. At the start of period 1, nature draws the type of drug store and the drug store sets d_1.

2. Consumers then decides whether to buy antimalarial drugs based on their prior (θ) from the store in their village or travel to a nearby village to purchase drugs.

3. Consumers receive a signal about the quality on the market $s = d_1 + z$ and update their beliefs ($\hat{\theta}$) about the likelihood that the seller in their village is honest.

[14]Intuitively, we can think of consumers gathering information from people around them who are sick and receive treatment. Each person is assessed, using the real line as unit of measurement, of how likely it is that they suffer from malaria and that the medicine they used was genuine. Aggregating this information provides the signal s.

[15]The third term also helps ensuring that the drug store's maximization program is convex.

4. At the start of period 2, the seller sets d_2.

5. Consumers buy from either the incumbent seller or from a seller in the nearby village.

6. Payoffs are realized.

We make two assumptions.

Assumption 1: The variable z has a normal distribution $N(0, \sigma_z^2)$ with variance σ_z^2 such that

$$\sigma_z^2 > \max\left\{\frac{\delta\Pi_2(c-\mu)}{4}, \frac{1}{2}\right\}$$

Assumption 2: Let $c-1 < \mu < c < 1$, $\frac{1-c}{c-\mu} > \frac{1}{2}$, and $\mu < \frac{1}{\phi}\left(c\phi - 1 + \sqrt{2\phi^2(c-1)+1} - 1\right)$ with $\phi = \frac{\delta}{\sqrt{2\pi\sigma_z^2}}$ for opportunistic types.

Assumption 1 imposes that there is sufficient noise in the observation of drug quality to ensure the convexity of the drug store sellers' maximization problem. Assumption 2 restricts the parameter space to ensure an interior solution in the monopoly scenario and also implies that $\Pi_2(c-\mu) > 0$; i.e. that short-run profit maximization yields positive profits. Both assumptions are sufficient but not necessary.

3.2 The monopoly case

Proposition 1: In equilibrium, the opportunistic seller sells some fake drugs and the share of fake drugs is falling in the moral cost μ and increasing in the variance of the noise term σ_z^2.

The solution concept is PBE (see appendix for details). We solve the problem by working backwards. In the last period, assuming the firm is still on the market, the seller maximizes $\Pi_2(d_2)$. Consequently, an opportunistic will set $d_2^O = c - \mu$, where $0 < d_2^O < 1$ by assumption 2.

Consider then period 1. When making their first purchase consumers base their decision only on their prior (θ).[16] Let consumers' expectation of the sellers' choice of d_1 conditional on type T, be h and o for the honest and opportunistic types, respectively.

[16]When consumers are indifferent between buying from the seller in their own village or in the nearby village we assume they will buy from the store in their own village.

Given the prior θ, and the signal s, Bayesian updating gives the posterior that the incumbent seller is honest:

$$\hat{\theta}(s) \equiv \Pr(H|s) = \frac{\theta f(s-h)}{\theta f(s-h) + (1-\theta) f(s-o)} \tag{1}$$

Consumers will purchase from the incumbent seller iff the posterior $\hat{\theta}(s)$ is greater or equal to their prior θ; i.e., if

$$\frac{\theta f(s-h)}{\theta f(s-h) + (1-\theta) f(s-o)} \geq \theta \,, \tag{2}$$

or

$$f(s-h) \geq f(s-o) \,. \tag{3}$$

As z is assumed to be normally distributed with mean 0, it follows that (3) is equivalent to

$$s \leq \frac{h+o}{2} \,. \tag{4}$$

Thus, the probability that the incumbent seller remains on the market; i.e., that consumers are still willing to buy, as a function of the seller's choice of fake drugs to sell d_1 is

$$P(d_1) = \Pr\left(d_1 + z \leq (h+o)/2\right) = F\left((h+o)/2 - d_1\right) \tag{5}$$

The opportunistic seller's maximization program in period 1, after substituting for equilibrium period 2 choices is then

$$\max_{d_1} \Pi = 1 - C(d) + \delta P(d_1) \Pi_2 (c - \mu)$$

The first-order condition is

$$(c-\mu) - d_1 - \delta f\left(\frac{h+o}{2} - d_1\right) \Pi_2 (c-\mu) = 0 \tag{6}$$

In equilibrium (rational expectations), we have $h = 0$ and $o = d_1^*$ so

$$(c-\mu) - d_1^* - \delta f\left(-\frac{d_1^*}{2}\right) \Pi_2 (c-\mu) = 0 \tag{7}$$

The first-order condition implicitly defines $d(\sigma_z^2, \mu)$. Applying the implicit function theorem to the first-order condition yields

$$\frac{\partial d(\sigma_z^2, \mu)}{\partial \sigma_z^2} > 0; \ \frac{\partial d(\sigma_z^2, \mu)}{\partial \mu} < 0$$

Drug stores trade off the short run gain of selling bad quality with the long term cost of not having any demand in period 2 (exit). If the variance of the noise term σ_z^2 is not too low, and given assumption 1, there exist an interior solution where the opportunistic sellers sell some fake drugs (see appendix). An increase in μ increases the cost of selling bad quality and as a result, drug quality increases. Greater noise in the signal about quality implies that the signal carries less weight and as a consequence consumers respond (update) to a lesser extent to changes in quality; i.e., the larger is σ_z^2, the lower the marginal return to quality.

3.3 Introducing competition

Assume there are two sellers on the market of which one is committed to selling high-quality antimalarials. That is, the second seller is assumed to be an honest type that mechanically sets $d = 0$. Given the empirical setting in this paper, we label the second seller the NGO and the first seller as the incumbent.

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; i.e., consumers believe the incumbent and the NGO can both be of two types (H and O). As both sellers in period 1 are perceived as being equally likely to be an honest type, we assume half of the consumers buy from the incumbent and half of the consumers from the NGO in period 1.[17] To simplify the analysis, we assume the incumbent can observe the NGO's type (and vice versa).[18]

With the entry of the NGO, consumers now receive two possibly correlated signals, s^i and s^n, where s^i [s^n] is a signal of the amount of fake drugs being sold by the incumbent [NGO], with $s^i = d_1^i + z^i$ and $s^n = d_1^n + z^n$. Both noise variables, z^i and z^n, are normally distributed with mean 0 and variance σ_z^2.

[17] In the experiment we discuss below, the NGO branded itself as a high quality seller by using the brand name of the funding organization. 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 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.

[18] This assumption can be relaxed without qualitatively affecting the key results.

The incumbent seller now faces two constraints when setting quality. A too low quality might cause consumers to buy from the seller in the nearby village. A too low quality might also cause consumers to buy from the NGO only. Given the symmetry in beliefs across sellers, and as the NGO always sets $d^n = 0$, only the second condition is relevant.

Before making their second purchase, consumers receive signals s^i and s^n. Consumers will buy from the incumbent iff

$$s^i \leq s^n \tag{8}$$

The probability that consumers prefer to buy from the incumbent (as opposed from the NGO) is thus

$$\Pr\left(d^i + z^i \leq z^n\right) = G\left(w \leq -d^i\right)$$

where $G(w)$ is the distribution function for $w = z^i - z^n$ and w is normally distributed with mean zero and variance $\sigma_w^2 = 2\sigma_z^2(1-\rho)$ and where $\rho < 1$ is the correlation between noise terms.

The opportunistic incumbent's maximization program in period 1, after substituting for equilibrium period 2 choices is

$$\max_{d_1} \Pi = \frac{1}{2}\left[1 - c(d_1^i)\right] + \delta G(-d_1^i)\Pi_2(c-\mu) \tag{9}$$

Proposition 2: With the NGO in the market, and for a sufficiently high precision of the signal w (ρ large), opportunistic firms with $\mu \leq \bar{\mu} \equiv c - \sqrt{\frac{2\delta(1-c)}{1-\delta}}$ (low moral cost types) will set low quality ($d_1^* = c - \mu$) and be forced to exit after period 1; firms with $\bar{\mu} < \mu < c$ (medium moral cost types) will mimic the NGO and set $d_1^* = 0$. Firms with $\mu \geq c$ will continue selling authentic drugs ($d^* = 0$).

The intuition for this results can easily be illustrated in the extreme case where $\rho = 1$. In that case, relative signals $s_i/s_n = d_{i1} + 1$, so if the seller set $d_{i1} > 0$, $s_i/s_n > 1$ and the incumbent seller will be revealed as an opportunistic type with probability 1. The incumbent thus faces the choice of setting $d_{i1} = 0$ and mimicking the NGO or maximizing short run profits by setting lower quality and exiting the market after period 1. Mimicking the NGO is optimal provided that the reputational gains outweigh the costs; i.e., if $\mu \leq \bar{\mu} \equiv c - \sqrt{\frac{2\delta(1-c)}{1-\delta}}$.[19] That is, drug stores that sells authentic quality ($d = 0$) before the intervention; i.e. in the monopoly case, will continue to do so, while drug stores that sell

[19]The model also has additional predictions. For example, one can show that the entry of the NGO will cause all opportunistic firms to raise quality in the extreme case when z^i and z^n are orthogonal; i.e. $\rho = 0$. Furthermore, and increase in ρ, starting at $\rho = 0$, leads to higher quality.

relatively few fake drugs (sellers with $\mu \in (\bar{\mu}, c)$) will increase quality and those that sell relatively low quality (sellers with $\mu \leq \bar{\mu}$) will exit the market.

4 Design, Intervention, and Measurement

4.1 Power and design

The drug quality trial was embedded in the roll-out of a randomized evaluation of a market-based community health care program – the CHP program – in Uganda (Björkman-Nyqvist, Guariso, Svensson, and Yanagizawa-Drott, 2015). For the CHP program, the sample size was set to detect a reduction in overall under-five mortality. In total, 214 villages (clusters) were selected across 10 districts. The villages were stratified by location (district) and population size, thus creating matched blocks with similar characteristics. From each block, villages were then randomly assigned to an intervention and a comparison group.

For the drug quality trial, the sample size, i.e.; the number of villages (districts) to include from the CHP trial, was determined to detect a reduction in the number of drug stores selling fake ACT medicine. No baseline data on the core outcome variable existed in Uganda and due to the tight time schedule for the roll-out of the CHP program, such data could not be collected prior to the start of the intervention. Thus, power calculations had to be determined from assumption of standardized differences; i.e. the minimum detectable effect size divided by the standard deviation.

Balancing the need to have sufficient power of the design with logistical and cost concerns, a design with 100 villages, of which half were allocated to the intervention group, was deemed appropriate. Such a design had 80% power to detect a 0.5 [0.56] standardized difference between the intervention and the control group at the two-sided 10% [5%] significance level.

Consequently, four districts (Bushenji, Mbale, Mbarara, and Mpigi), with 99 experimental villages, were selected from the CHP trial. All four districts were characterized by high and endemic *P. falciparum* malaria prevalence (Figure 2). Half of the villages had been randomly assigned to the intervention group (49 villages) and the remaining villages (50 villages) had been assigned to the control group.

A census of drug shops was implemented in all 99 trial villages in 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.

The trial profile is illustrated in Figure 3. A baseline household survey and a census

of shops were implemented in the beginning of 2010. At the end of 2010, approximately a year 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. 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.

4.2 Intervention

Once the treatment status was assigned, the collaborating NGOs 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.

The saleswomen are expected to sell ACTs to households in the village to which they were assigned. Some contamination might however have occurred, most likely causing us to estimate a lower bound on the impact of the market entry. Importantly, the NGO carried 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), and were instructed to conduct home visits for sick children, to visit newborns within the first 48 hours of life, and to encourage pregnant women to deliver in a facility or with professional assistance. While it is possible that these additional tasks could have an effect on the quality of ACTs in the market place, the sale of hygiene products or deworming pills or home visits of newborn and sick children would likely not have a first-order effect on these outcomes. The saleswomen did not have access to any diagnostic tests for malaria and they did not receive any training about the extent and dangers of counterfeit ACTs.

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

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 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

[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 (if authentic). In these cases, the covert shopper acquired the least expensive brand.

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

[24]Nine out of the ten largest pharmaceutical companies worldwide rely on Raman spectroscopy technology to authenticate inputs. Moreover, a growing number of national drug enforcement agencies use the TruScan Raman Spectrometer to test for counterfeit and substandard medicines.

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 set prior beliefs in a manner consistent with the data, the inspectors were informed of the share of fake in total in the sample they were asked to assess.

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".

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]

5 Results

5.1 Summary statistics

Balance tests

Table 1 reports mean pre-treatment characteristics for the intervention and control groups, along with test statistics for the equality of means. Panel A uses the full sample of 99 villages while Panel B uses data from the sample of 57 villages with drug shops at baseline.

There is no systematic difference between the intervention and the control group at baseline and most differences are small. Thus, the random assignment of villages appears to be successful. 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 intervention 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 intervention 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 be-

[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.

ing effective by most households in both groups.[26] 28 percent (26 percent in the control group) of the households believe the nearest drug shop sells fake antimalarial drugs and 32 percent (36 percent 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 194 households (199 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 higher in the control group, the differences between the groups are not statistically significant. As the number of drug shops may influence the likelihood of fake drugs being sold, we include the number of drug shops in the vector of pre-intervention village-specific covariates.[27]

The means are similar in the smaller sample of villages with a drug store at baseline (Panel B). As in the full sample, the means are also balanced across intervention and control villages on essentially all outcomes. The means are also similar to the full sample.[28]

Prevalence of fake drugs

How common are counterfeit and substandard ACTs? Table 2 provides summary statistics of the prevalence of fake drugs in the control group. 36.8 percent of the outlets sell fake ACTs and fake ACTs are sold in 0.42 stores per village.[29] The prevalence is highest in the western, and most rural, districts (Bushenyi and Mbarara), and 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.[30]

The last rows in Table 2 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

[26]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.

[27]We also include village size (number of households) and a measure of demand for ACT drugs (share of households that believes ACT is highly effective) as additional controls.

[28]The main difference, by comparing means across the two samples and noting that panel B is a subset of Panel A, is in the source of ACTs. In villages with a drug store, 20 percent (or 10 percentage points) more household acquire ACT drugs from private drug shops as compared to villages without a drug shop.

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

[30]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.

A key assumption in the model is that quality cannot be directly observed. Table 3 provides evidence in favor of this assumption. In columns (1)-(2) we use data collected from visual inspection by ten surveyors. There is little evidence that observable characteristics can reveal quality. While the coefficients are positive, the point estimates are relatively small and not statistically significant at conventional levels.

In the model, drug stores compete in quality but not in 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.[31]

5.2 Experimental evidence: Reduced form

Can good products drive out bad? We start by presenting intention-to-treat (ITT) estimates using the 99-villages sample; i.e., we use the sample of all experimental villages including those with no drug shops at baseline.[32] The dependent variable here is number of drug shops selling fake drugs in the village. The simple treatment-control difference, controlling for the stratified random design using district fixed effects, is -0.26. That is, the intervention reduced the number of private drug shops selling fake ACT drugs by 63% (Table 4, column 1), or by 0.64 standard deviations. The difference is smaller, -0.20, when controlling for number of baseline drugs shops, village size, and a proxy of demand for ACTs. However, the difference is still quantitatively large – a 46% fall in number of shops selling fake drugs – albeit somewhat less precisely estimated (column 2). Number of drugs shops is a count variable. In column (3) we therefore estimate a Poisson model. The treatment effect is highly significant and the incidence ratio reported in the last row

[31] 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. Regressions without village fixed effects confirm there is no positive correlation between quality and price (the point estimate is negative; result available upon request).

[32] In the 99-villages sample, 42 villages did not have a drug shop within the village boundary at baseline.

implies a 64% reduction in the number of shops selling fake drugs in the treatment as compared to the control group.

Columns 4-6 use the core sample of 135 drugs shops identified at baseline to estimate reduced form effects from increased competition. These reduced form effects capture both changes on the extensive margin (exit of drug shops from the market for ACTs) and changes on the intensive margin (changes in behavior by outlets remaining in the ACT market). The entry of the NGO resulted in a 15.3-16.9 percentage points reduction in the share of stores selling fake drugs and the point estimates are precisely estimated (columns 4-5). That is, out of the total stores at baseline, more than 50% either stopped selling ACTs or switched from selling fake drugs to authentic drugs.

5.3 Mechanisms

The results so far show that the entry of the NGO resulted in a large reduction in the share of private drug shops selling fake ACT drugs. The model identifies two mechanisms through which this reduction could come about: Exit of drug shops selling bad quality ACTs from the market (extensive margin) or a switch from selling low quality to high quality drugs (intensive margin).

Given the available data, we cannot directly estimate these two mechanism. However, we can bound the effects by imposing structure derived from the model in section 3. We present the results of two complementary approaches.

Extrapolating bounds from reduced form regressions

In the model, firms differ with respect to the moral cost of selling bad quality, μ. Facing competition, different types of firms react differently. Specifically, firms with a moral cost $\mu < \bar{\mu}$ will sell a high share of fake drugs and thus be revealed as bad sellers and forced to exit. Firms with a moral cost $\bar{\mu} < \mu < c$ will remain in the market but increase quality to mimic the NGO, and firms with a moral cost $\mu > c$ will remain in the market and continue to sell authentic drugs. Thus in the model, only the low moral cost types exit. In reality, of course, firms may exit also for other reasons. Assuming these other reasons for exit are orthogonal to the type of the firm, we can derive a upper bound on the extensive margin effect from the reduced form regressions reported in table 3. To see this consider the following simple data generation model.

Let X_J^D denote the total number of stores in group J, with $J = \{T, C\}$ (treatment, control) at baseline selling drugs of type D, with $D = \{F, A\}$ (fake, authentic). We assume $X_J^F / X_J = \tau$ for $J = \{T, C\}$, i.e., the share of fake-selling shops out of the total number of shops is the same across groups at baseline. This is a natural assumption to make given

that the villages were randomly assign into treatment.

Assume then that between baseline and the time the drugs shops were subject to the quality test, a share δ of the stores randomly exit. In the treatment group, and facing competition, an additional share α_E selectively exit (firms with $\mu < \bar{\mu}$) and a share α_I switch from selling fake to authentic drugs (firms with $\bar{\mu} < \mu < c$), with $\delta + \alpha_E + \alpha_I \leq 1$. If differential exit between the treatment and control group is driven by the selective exit of stores selling fake drugs at baseline, then in our core sample of all 135 drug shops identified at baseline, a share $(1-\delta)$ of the stores in the control group will remain in the market and a share $(1-\delta-\alpha_E)\tau + (1-\delta)(1-\tau)$ will remain in the treatment group. Further, a share $(1-\delta)\tau$ of the stores will sell fake drugs at the time of the drug quality survey in the control group and a share $(1-\delta-\alpha_E-\alpha_I)\tau$ will sell fake drugs in the treatment group. Thus, if we let y^E_{135} be a binary variable taking the value 1 if the store remained in the sample and sold ACT at the time of the drug quality survey, and 0 otherwise, and let y^I_{135} be a binary variable taking the value 1 if the store remained in the sample and sold fake ACT at the time of the drug quality survey, and 0 otherwise, and estimate the system (using the full sample with 135 store identified at baseline):

$$y^E_{135} = \beta_0 + \beta_1 T + \varepsilon \tag{10}$$

$$y^I_{135} = \gamma_0 + \gamma_1 T + \varepsilon \tag{11}$$

then

$$\beta_0 = (1-\delta) \quad \beta_1 = -\alpha_E \tau \quad \gamma_0 = (1-\delta)\tau \quad \gamma_1 = -(\alpha_E + \alpha_I)\tau \tag{12}$$

and

$$\alpha_E^{MAX} = -\frac{\beta_1}{\gamma_0/\beta_0}, \quad \alpha_I^{MIN} = -\frac{\gamma_1 - \beta_1}{\gamma_0/\beta_0}$$

where α_E^{MAX} is the (maximum) share of firms that selectively exit and α_I^{MIN} is the (minimum) share of firms that switch from selling fake to authentic drugs.

Structural model

Consider a simplified and empirically based version of the model discussed in section 3. Let q_i^* denote firm i:s choice of (normalized) quality and $b_i^* = -q_i^*$ define the choice of poor quality and let s_i^* denote the selection decisions (whether to stay in the market or exit). Both b^* and s^* are latent variables.

Assume firm i:s choice of quality, conditional on remaining in the market, can be writ-

ten as

$$q_i^* = \beta_0 + \beta_T T + \nu_i \tag{13}$$

or

$$b_i^* = \lambda_0 + \lambda_T T - \nu_i \tag{14}$$

where T is a treatment indicator. Further assume firm i:s choice of remaining in the market can be written as

$$s_i^* = \gamma_0 + \gamma_T T + \eta_i \tag{15}$$

The latent variables s^* and b^* (and q^*) are related to the observed binary bad quality and staying in the market indicators b and s according to

$$b_i = \begin{cases} 1 & \text{if } b_i^* > 0 \\ 0 & \text{if } b_i^* < 0 \end{cases} \tag{16}$$

$$s_i = \begin{cases} 1 & \text{if } s_i^* \geq 0 \\ 0 & \text{if } s_i^* < 0 \end{cases} \tag{17}$$

The two key parameters are γ_T – capturing the effect of the entry of the NGO on the firm's exit decision – and λ_T – capturing the firm's quality choice in response to the entry of the NGO. The model predicts that retailers are more likely to exit the market when facing competition and, conditional on staying, tend to increase the quality of the drugs sold. Thus, we expect $\lambda_T < 0$ and $\gamma_T < 0$.

Equations (16) and (17) define a binary-outcome selection model with identical explanatory variables. We can identify λ_T and γ_T by placing restrictions on the data generating process. Specifically, as summarized in proposition 2, the model also predicts that the (unobserved) moral cost of selling bad quality drugs influences both the likelihood to remain in the market – as retailers selling low quality are more likely to be detected and forced to shut down – and the quality if remaining in the market. The proposition is illustrated in Figure 2. Thus, we assume that the error terms in (14) and (15) can be decomposed into two terms;

$$\nu_i \Rightarrow \left[\mu_i, \varepsilon_i^q\right]; \eta_i \Rightarrow \left[\mu_i, \varepsilon_i^s\right] \; ; \tag{18}$$

where μ is the unobserved moral cost of incumbent sellers and ε^q and ε^s are unobserved random noise terms. We assume that $\mu \sim N(0, \frac{1}{\kappa})$, $\varepsilon^q \sim N(0, \frac{1}{1-\kappa})$, $\varepsilon^s \sim N(0, \frac{1}{1-\kappa})$, and $E[\mu\varepsilon^q] = E[\mu\varepsilon^s] = E[\varepsilon^q\varepsilon^s] = 0$, and that the error terms in equations (14) and (15) are linear combinations of the moral costs and the random noise terms; i.e., $\nu = \kappa\mu + (1-\kappa)\varepsilon^q$ and $\eta = \kappa\mu + (1-\kappa)\varepsilon^s$, where $\kappa \in [0,1]$. Then it follows that $\eta \sim N(0,1)$ and $\nu \sim N(0,1)$, and ν and η have a bivariate normal distribution with zero means, unit variances, and correlation coefficient $\rho = -\kappa$; i.e., $\rho \in [-1,0]$.

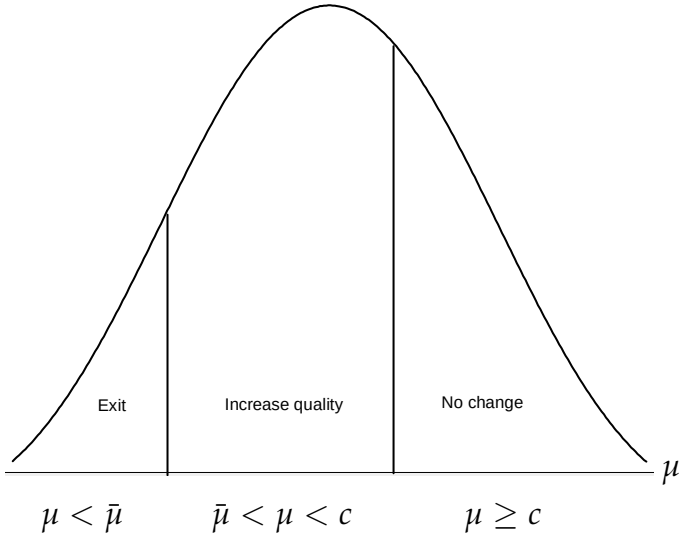

Figure 2: Impact of entry conditional on μ

The model (16)-(17) can be estimated by maximum likelihood. The construction of the log-likelihood function is straightforward as the data identify only three possible events,

$$(19) \qquad \begin{aligned} z_{i0} &= \begin{cases} 1 & \text{if } s_i = 0 \\ 0 & \text{otherwise} \end{cases} \\ z_{i1} &= \begin{cases} 1 & \text{if } b_i = 1 \text{ and } s_i = 1 \\ 0 & \text{otherwise} \end{cases} \\ z_{i2} &= \begin{cases} 1 & \text{if } b_i = 0 \text{ and } s_i = 1 \\ 0 & \text{otherwise} \end{cases} \end{aligned} .$$

Letting $\boldsymbol{\gamma} = (\gamma_0, \gamma_T)$ and $\boldsymbol{\lambda} = (\lambda_0, \lambda_T)$, the likelihood function can thus be written as

$$\begin{aligned} L &= I(z_{i0} = 1)\,\Phi\left(-\boldsymbol{\gamma}'\mathbf{x}_i\right) + I(z_{i1} = 1)\,\Phi_2\left(\boldsymbol{\gamma}'\mathbf{x}_i, \boldsymbol{\lambda}'\mathbf{x}_i, \rho\right) \\ &\quad + I(z_{i2} = 1)\left(\Phi\left(-\boldsymbol{\gamma}'\mathbf{x}_i\right) - \Phi_2\left(\boldsymbol{\gamma}'\mathbf{x}_i, \boldsymbol{\lambda}'\mathbf{x}_i, \rho\right)\right) \end{aligned}$$

where $\Phi(.)$ is the standard normal distribution function and $\Phi_2(.,.,\rho)$ is the bivariate

standard normal distribution function with correlation coefficient $\rho = -\alpha$.

The log-likelihood function is

$$\ln L(\gamma, \lambda) = \sum_{z_{i0}=1} \ln \Phi\left(-\gamma' \mathbf{x}_i\right) + \sum_{z_{i1}=1} \ln\left(\Phi_2\left(\gamma' \mathbf{x}_i, \lambda' \mathbf{x}_i, \rho\right)\right) + \sum_{z_{i2}=1} \ln\left(\Phi\left(-\gamma' \mathbf{x}_i\right) - \Phi_2\left(\gamma' \mathbf{x}_i, \lambda' \mathbf{x}_i, \rho\right)\right) \tag{20}$$

In estimating the model, we allow for district fixed effects to account for the stratified randomization procedure. To improve estimation precision and to account for chance differences between groups in the distribution of pre-random assignment, we also control for the same set of pre-intervention village-specific covariates as in the reduced form model in both the selection and outcome specifications.[33]

Results

The results are reported in table 5. Panel A reports maximum likelihood estimates from the joint estimation of the two linear equations (10) and (11). Under the assumption that the differential exit between the treatment and control group is solely driven by exit of stores selling fake drugs at baseline, we can estimate an upper bound on the exit channel effect, and a lower bound on the intensive margin effect. The estimates imply that the exit channel accounts for 46% of the total effect, while the intensive margin effects accounts for the remaining 56%.

Panel B and C report estimates of the structural approach at the boundary points, $\rho = -1$ and $\rho = 0$, respectively. Assuming that only low moral cost types exit ($\kappa = 1$ or $\rho = -1$), Panel B, the estimated exit channel parameter γ_T and estimated intensive margin channel parameter λ_T are both significantly negative. Consistent with the estimates reported in Panel A, the exit channel accounts for approximately half of the total effect.[34]

Panel C reports the findings with $\kappa = 0$ (or $\rho = 0$); that is, when the error terms in equations (14) and (15) are statistically independent. Assuming that the error term in the selection equation is orthogonal to the error term in the intensive margin equation implies that we estimate a lower bound on the exit effect. In this scenario, the intensive margin effect accounts for approximately 70% of the total effect.

Figure 4 plot the relative effects of the exit and intensive margin channel for different

[33] Sartori (2003) shows that the MLE of the binary-outcome selection model with identical explanatory variables and a given ρ is consistent and asymptotically normal provided that at least one of the independent variables are continuous without any mass points and that $\gamma \neq \lambda$.

[34] The total effect is $\Delta(s) + (1 - \Delta(s))\,\Delta(b)$, where $\Delta(s)$ is the difference between the treatment and the control group in the probability of remaining in the market; i.e.; $\Phi(\gamma_0 + \gamma_T T) - \Phi(\gamma_0)$, and $\Delta(b)$ is the difference between the treatment and the control group in the probability of selling bad quality, conditional on being on the market; i.e., $\Phi(\lambda_0 + \lambda_T T) - \Phi(\lambda_0)$.

values of κ (or ρ). Intuitively, as κ falls (ρ increases in absolute terms), we allow for an increasing share of all types of firms to exit the market, not just low quality ones. As a result, the relative effect of the intensive margin effect rises, while the relative effect of the exit margin effect falls. As shown in Figure 4, while an increase in ρ, initially increase the magnitude of the intensive margin relative the exit margin channels, the increase quickly levels of. For example, at $\rho = -3/4$, the intensive margin channel accounts for $2/3$ of the total effect.

5.4 Secondary outcomes: Learning and demand

Learning

The entry of the NGO resulted in higher mean quality in the ACT drugs sold by private retailers. In the model, reputation forces mean that incumbent sellers' incentives to increase quality (or exit the market) are driven by consumers' increased ability to learn about the quality of the drugs sold by the incumbent following the entry of the NGO. In this section we provide evidence in support of this mechanism.

Table 6, columns 1-4, exploit cross-sectional household data collected at endline to estimate the share of households that believes the nearest incumbent drug shop sells fake drugs. Consistent with the reduction in low quality ACT drugs, and learning, we find that households in intervention villages were approximately 7 percentage points, or 19%, less likely to believe that incumbent shops sell fake antimalarials as compared to control villages.

Columns 5-8 report difference-in-differences estimates, using the full sample of baseline data (57 villages with drug shops at baseline). The difference-in-differences estimates implies a 11-12 percentage points (columns 5-6) reduction in the subjective likelihood that the incumbent drug store sells fake drugs; or a 43-45% (33-34%) reduction as compared to the control group mean at baseline (endline). Thus, the decrease of fake drugs in outlets was accompanied by an improvement in reputation, consistent with learning.

Note that, interpreted within our simple theoretical framework, there are two complementary mechanisms that produce the result that the NGO entry affects both average quality and the reputation of drug shops? 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 after treatment with drugs from the NGO with outcomes for after treatment with drugs from the incumbent). 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.[35]

Demand

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, 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 17 percent (from an average baseline price of 8910 Ugandan shillings in control villages to approximately 7400 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 average price among drug shops and the NGO price decreased from about 27 percent to 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.

Table 8 estimates the effects on ACT quantity using data from the household survey on treatment of children reported sick in malaria using either endline data (columns 1,3,5) or combining the full baseline data with endline data (columns 2,4,6).[36] Columns 1-2 show that there is no evidence of entry affecting the likelihood of sick children being treated with ACTs, as compared to treatment with non-ACT antimalarials.[37] It is common practice, however, to buy less than a full dose and outlets typically offer a price per pill. Columns 3-4 show that the entry of the NGO affected the intensity of ACT treatment and households in the treatment villages are more likely to have treated their child with full ACT dose. The estimates imply that conditional on ACT treatment households acquired 2-2.4 more pills per sick child. From a baseline of 6.8 pills in control villages, this implies a 29-35% increase in ACT quantity. This suggests that the NGO entry increased the total size of the market for ACTs. Perhaps unsurprisingly, columns 5-6 further shows 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

[35]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).

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

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

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).[38]

5.5 Alternative mechanisms and robustness

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 saleswomen did not have access to any diagnostic tests for malaria and they did not receive any training about the extent and dangers of counterfeit ACTs. The self-reported rate of malaria is also similar across the treatment and the control groups.

In appendix, Table A.1, we report treatment effects on knowledge about antimalarial medicines, in particular whether ACTs are more effective than non-ACTs. The point estimates are close to zero and insignificant. Thus, health education does not seem to explain the findings.[39]

Another potential mechanism would be that the NGO informed households about

[38] 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.

[39] We also find no effects on knowledge and misconceptions about what causes malaria (results not included for brevity).

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 the 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. It is also possible that drug shop owners learn that they sell bad quality drugs as a result of the entry of the NGO, and therefore switch retailer and as a consequence quality increases. Our data does not allow us to assess wholesaler behavior. However, the model could be extended (or reinterpreted) to take this alternative mechanism into account by having wholesalers determining quality and retailers only setting prices. In this alternative model, there would be two types of wholesalers (honest and opportunistic) that can provide retailers with antimalarial drugs of quality d. Bayesian consumers, and retailers, would then update beliefs about the type of wholesaler, conditional on observing the share of people that recovered quickly. The mechanism through which bad quality drugs are driven out of the market would, in this alternative version of the model, be very similar to the model presented in section 3. While it may not matter for household members seeking treatment for malaria whether retailers or wholesalers are cheating, it is still an important issue for further research.

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 leads 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.[40]

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*; i.e., would quality in the market place increase if the NGO entered and sold drugs of the same (low) quality as the market. The observational data presented in Table 2, however, 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 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.

6 Conclusion

To our knowledge, this is the first study to use a randomized intervention to study the determinants of drug quality in developing countries. We document that the market for antimalarial medicines in Uganda is plagued by low quality, and provide evidence that entry by an NGO that sold a superior product had a significant impact on the market equilibrium. While assessing the total welfare impact is beyond the scope of our study, the results on quality, price and quantity demanded make it quite clear that such entry can substantially increase consumer surplus. Moreover, a long-term follow up study by Bjorkman-Nyqvist, Guariso, Svensson, Yanagizawa-Drott (2015) provides complementary evidence that the intervention improved health outcomes, including child mortality. While health outcomes are likely not solely driven by the improved market equilibrium consisting of higher quality and lower price, together the studies indicate that finding feasible and scalable solutions to fix dysfunctional markets for medicines is of first-order importance for policymakers.

Antimalarial medicines 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 pharmaceuticals. Evidence and news reports suggest that product quality in markets for experience goods more broadly, such as fertilizers and seeds, gasoline, auto

[40]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, suggesting that the quality results are not driven by entry price differences (results available upon request).

parts, electronics, baby food, and hygiene products (Mwakalebela, 2012; Tentena, 2012; Rajput, 2012; OECD, 2008), is notoriously low in developing countries. Studying the markets for these products is important because poor quality arising from weak incentives for building reputation can have adverse welfare consequences not only by affecting health outcomes, but also productivity and people's willingness to experiment and adopt new technologies. Our study indicates that while reputations forces matter, the fact that a large share of retailers sold low quality products in the absence of the intervention indicates that reputation building is a low return investment, arguably because learning is very noisy for consumers. A recent study by Bai (2015) finds similar results, using experimental variation and structural estimation methods to investigates the quality of food in the watermelon market in China. In addition, evidence from the market for agricultural inputs (fertilizers and hybrid seeds) in Uganda by Bold et al. (2015) shows that quality - but not prices - varies tremendously across retailers and that while high quality products are profitable to adopt, returns are negative for a non-trivial share of the quality distribution in the market. The negative productivity consequences of weak incentives for building reputation are quite clear. Thus, understanding the feasibility and cost-effectiveness of alternative interventions to improve reputation building mechanisms in these markets are important from a policymaking perspective, and to this end more research is needed.

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Online appendix

Appendix A: Proof of propositions

Proposition 1: Differentiating (6) yields

$$-1+\delta f'(.)\,\Pi(c-\mu)$$

so a sufficient condition for a maximum is that

$$\left|f'(s_1)\right|<\frac{1}{\delta\Pi(c-\mu)}$$

Note that for a normal distribution max $|f'(s_1)|$ is $\frac{1}{\sqrt{2\pi e\sigma^2}}$, so a sufficient condition for $s.o.c.<0$ is that $\frac{1}{\sqrt{2\pi e\sigma^2}}<\frac{1}{4\sigma^2}<\frac{1}{\delta\Pi(c-\mu)}$; i.e., if $\sigma_z^2>\frac{\delta\Pi(c-\mu)}{4}$ as is assumed (assumption 1). An interior solution in the domain $d\in(0,1)$ exists if $(c-\mu)-\delta f(0)\Pi(c-\mu)>0$; i.e., if $0<(c-\mu)<1$ and $\mu<\frac{1}{\phi}\left(c\phi-1+\sqrt{2\phi^2(c-1)+1}\right)$ with $\phi=\frac{\delta}{\sqrt{2\pi\sigma_z^2}}$ which is assumed (assumption 2).

Applying the implicit function theorem to (6) yields

$$\frac{\partial d\left(\sigma_z^2,\mu\right)}{\partial\sigma_z^2}=\frac{\frac{1}{\sigma^2\sqrt{2\pi\sigma^2}}e^{-\frac{d^2}{8\sigma^2}}\left(\frac{d^2}{8\sigma^2}-\frac{1}{2}\right)\delta\Pi(c-\mu)}{s.o.c.}$$

$$\frac{\partial d\left(\sigma_z^2,\mu\right)}{\partial\mu}=\frac{1-\delta f\left(-d/2\right)(c-\mu)}{s.o.c.}$$

$\partial d/\partial\sigma_z^2$ is positive if $\frac{d^2}{8\sigma^2}<\frac{1}{2}$. A sufficient condition for this is that $\sigma_z^2>\frac{1}{4}$ (which is assumed, assumption 1). $\partial d/\partial\mu$ is negative provided that $1/\delta>f\left(-d/2,\bar{\sigma}_z^2\right)(c-\mu)$. A sufficient condition for this is that $1>f(0)$; i.e., that $\sigma_z^2>\frac{1}{2\pi}>\frac{1}{4}$ (which is assumed, assumption 1).

Proposition 2: Note that $G(0)=\frac{1}{2}$ and that $\lim_{\rho\to1}G(x)_{x\neq0}=0$. Thus when ρ is sufficiently high, the firm has two strategies: Either maximizing first period profit (by setting $d_1=c-\mu$) or mimicking the NGO (by setting $d_1=0$). Mimicking the NGO is optimal iff

$$\Pi_1(0)+\delta\Pi_2(c-\mu)\geq\Pi_1(c-\mu)$$

That is if

$$\mu\geq\bar{\mu}\equiv c-\sqrt{\frac{2\delta}{1-\delta}(1-c)}$$

For sellers with $\mu < \bar{\mu}$, the best response as $\rho \to 1$ is to set $d_1 = c - \mu$ and be revealed as opportunistic with certainty while the best response for sellers with $\mu \geq \bar{\mu}$ is to mimic the NGO and set $d_1 = 0$.

Figure 1. Examples of 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

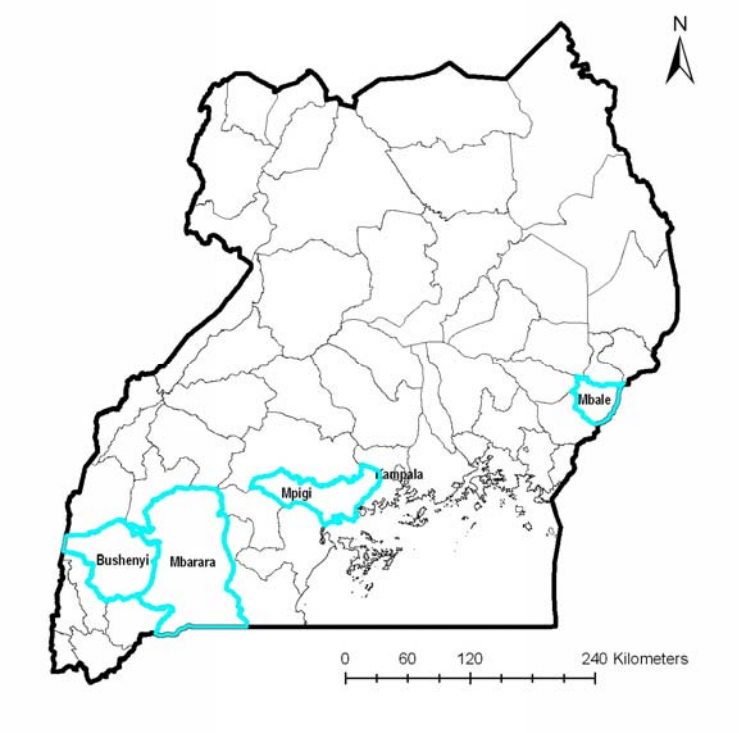


Figure 3: Trial profile

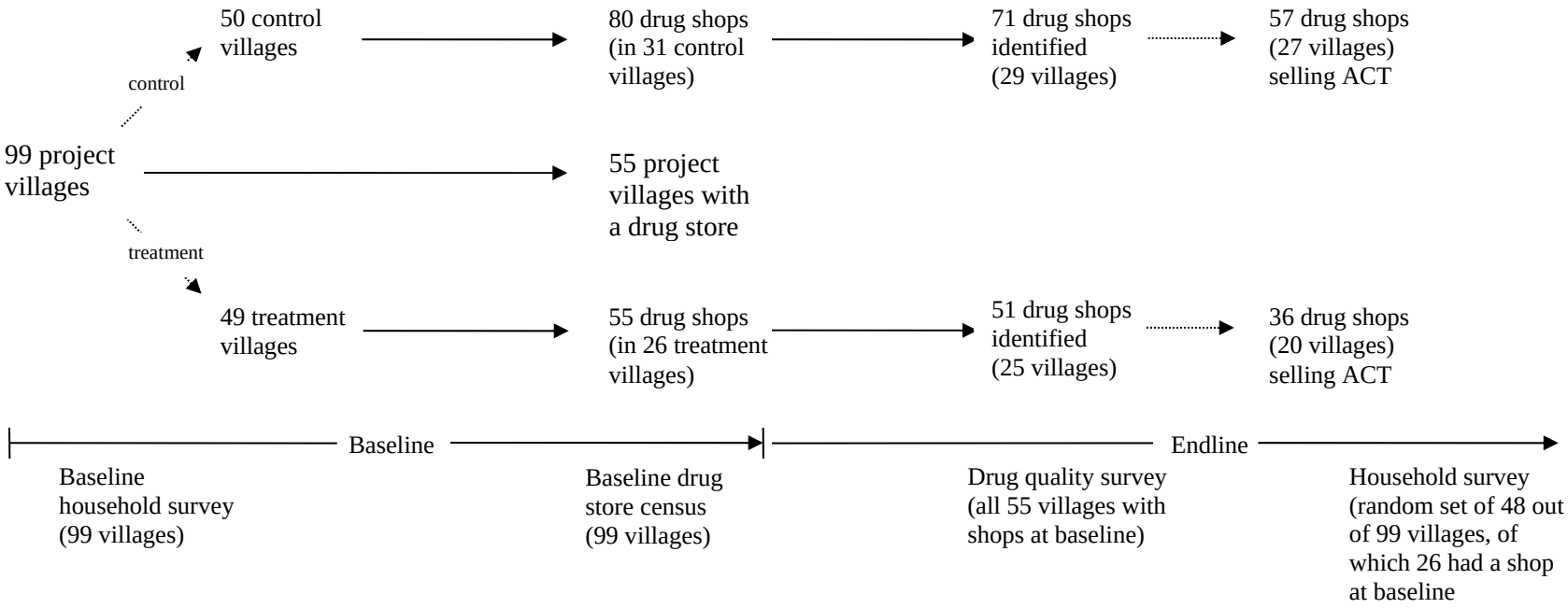
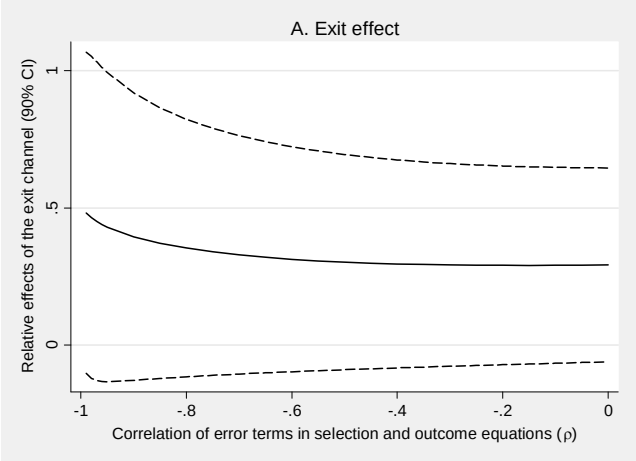


Figure 4: Relative effects of the exit and intensive margin channels



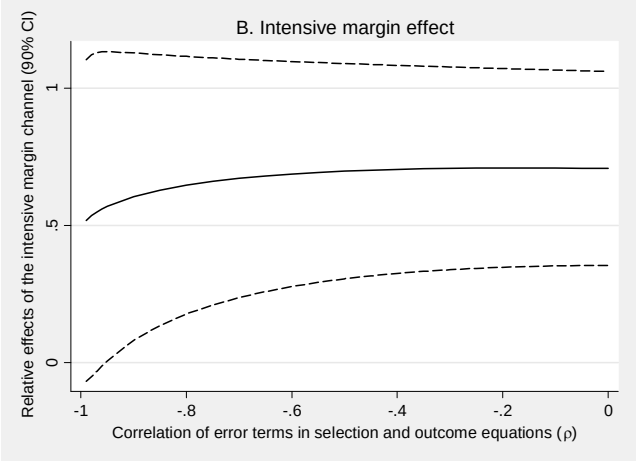


Table 1. Baseline Characteristics

	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
Village Characteristics										
Number of households in the village	99	193.6	199.3	-5.65	0.89	57	199.2	230.2	-22.8	0.68
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.

Table 2. Prevalence of Fake Antimalarial Drugs

	Drug shops selling fake drugs	Share of tested drugs that are fake		Number of drug shops selling fake drugs in the village	
	(1)	(2)	(3)	(4)	(5)
		All shops	Conditional	All villages	Conditional
All districts	36.8%	19.4%	51.5%	0.42	0.68
	(N=57)	(N=346)	(N=130)	(N=50)	(N=31)
By district					
Bushenyi	40.0%	30.0%	75.0%	0.80	1.33
Mbale	33.3%	11.1%	33.3%	0.33	0.55
Mbarara	53.3%	25.6%	47.9%	1.33	1.33
Mpigi	26.1%	14.1%	50.0%	0.20	0.38
By local competition					
Monopoly	30.8%	15.9%	46.4%	-	0.38
Competition	38.6%	20.5%	52.9%	-	0.84

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. In columns 4-5 the unit of analysis is a village and N thus referes to the number of villages. In column 5, the sample is restricted to villages with a drug shop at baseline. Competition implies that there are more than one drug shop selling ACT in the village.

Table 3. Correlates of Quality: Price and Observable Characteristics

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

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. OLS regressions in all columns. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

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

Dependent Variable:	Number of drug shops selling fake drugs in the village			Drug shop sells fake drugs, dummy		
Method	OLS	OLS	Poisson	OLS	OLS	Logit
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.263**	-0.195*	-1.031**	-0.153**	-0.169**	-1.102**
	(0.118)	(0.106)	(0.469)	(0.072)	(0.066)	(0.480)
Observations	99	99	99	135	135	135
R-squared	0.23	0.38	-	0.08	0.10	-
Unit of Analysis	Village	Village	Village	Drug shops	Drug shops	Drug shops
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	No	Yes	Yes
Dep. Var. Mean in Control	0.420	0.420	0.420	0.263	0.263	0.263
Incidence ratio, Odds Ratio	-	-	0.357	-	-	0.332

Note: In columns 1-3 the unit of analysis is a village using the sample of all 99 villages. In columns 4-6 the unit of analysis is a drug shop, where the sample contains all shops identified during the baseline shop census.The dependent variables are: in columns 1-3, the number of drug shops in the village that sold ACT that failed the Raman Spectroscopy authenticity tests; in columns 4-6, a dummy indicating if the drug shop sold failed drugs during the quality survey, and zero otherwise (including cases where the shop was not open or did not sell ACT). *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: number of drug shops at baseline, number of households at baseline, and share of baseline households that believe ACT are highly effective. Robust standard errors in parentheses, clustered at the village level (columns 4-6). *** 1% , ** 5% , * 10% significance.

Table 5. Maximum likelihood estimates

Name	Parameter	Estimate
Panel A: Bounds from reduced form linear regressions		
Exit effect	α_E^{MAX}	0.209
		(0.184)
Intensive margin effect	α_I^{MAX}	0.249
		(0.199)
Relative effect of the exit channel	$\alpha_E^{MAX}/(\alpha_E^{MAX}+\alpha_I^{MAX})$	0.456
		(.394)
Relative effect of the intensive margin channel	$\alpha_I^{MAX}/(\alpha_E^{MAX}+\alpha_I^{MAX})$	0.544
		(0.394)
Panel B: Bounds from binary-outcome selection model, ρ(κ) = -1		
Exit effect	γ_T	-0.296*
		(0.177)
Intensive margin effect	λ_T	-0.287*
		(0.174)
Relative effect of the exit channel	$\Delta(s)/(\Delta(s)+(1-\Delta(s))\Delta(b))$	0.505**
		(0.254)
Relative effect of the intensive margin channel	$\Delta(b)/(\Delta(s)+(1-\Delta(s))\Delta(b))$	0.495*
		(0.254)
Panel C: Bounds from binary-outcome selection model, ρ(κ) = 0		
Exit effect	γ_T	-0.239
		(0.208)
Intensive margin effect	λ_T	-0.696**
		(0.300)
Relative effect of the exit channel	$\Delta(s)/(\Delta(s)+(1-\Delta(s))\Delta(b))$	0.295
		(0.215)
Relative effect of the intensive margin channel	$\Delta(b)/(\Delta(s)+(1-\Delta(s))\Delta(b))$	0.707*
		(0.215)

Note: Sample includes all 135 shops identified during the baseline shop census, of which 93 shops sold ACT at endline. See text for details. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Table 6. Effects of NGO Entry: Consumer Beliefs About Drug Quality of Incumbent Shops

	Dependent Variable: Believes nearest drug shop sells fake drugs							
	Dummy	Dummy	Dummy	Likert Scale	Dummy	Dummy	Dummy	Likert Scale
	OLS	OLS	Logit	Ord. Logit	OLS	OLS	Logit	Ord. Logit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO entry	-0.065**	-0.065*	-0.304**	-0.286*	0.019	0.026	0.154	0.147
	(0.028)	(0.033)	(0.145)	(0.154)	(0.031)	(0.029)	(0.153)	(0.157)
NGO entry*Post-survey					-0.112**	-0.116**	-0.578**	-0.539**
					(0.051)	(0.050)	(0.243)	(0.246)
Observations	674	674	674	674	2397	2397	2397	2397
R-squared	0.01	0.01	-	-	0.04	0.05	-	-
Unit of Analysis	HH	HH	HH	HH	HH	HH	HH	HH
Survey Data	Post Only	Post Only	Post Only	Pre & Post	Pre & Post	Pre & Post	Pre & Post	Pre & Post
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Post-survey Dummy	No	No	No	No	Yes	Yes	Yes	Yes
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline
Number of villages	26	26	26	26	57	57	57	57
Dep. Var. Mean in Control	0.34	0.34	0.34	0.34	0.26	0.26	0.26	0.26
Odds Ratio	-	-	0.74	0.75	-	-	0.56	0.58

Note: The unit of observation is the household. The sample in columns 1-4 contains endline survey data, from villages with drug shops at baseline. Columns 5-8 add baseline data from villages with drug shops at baseline. The dependent variable is the answer to the survey 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. The control variables are: number of drug shops at baseline, number of households at baseline, and share of baseline households that believe ACT are highly effective. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.

Table 7. Effects of NGO Entry: Price

Dependent Variable:	Log(Price, Ush)		Price, '000 Ush	
	(1)	(2)	(3)	(4)
NGO entry	-0.146**	-0.160***	-1.45**	-1.58***
	(0.058)	(0.050)	(0.56)	(0.50)
Observations	93	93	93	93
R-squared	0.53	0.57	0.52	0.56
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop
District FE	Yes	Yes	Yes	Yes
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 consists of all shops that sold ACT at the time of the drug quality survey. The dependent variable is the price for a full dose of ACT. The control variables are: number of drug shops at baseline, number of households at baseline, and share of baseline households that believe ACT are highly effective. OLS is used in all regressions. 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:	Treated with ACT, dummy		# ACT pills, any source		# ACT pills, sourced from drug shops	
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.007	0.057	1.986***	-0.346	0.394	0.365
	(0.063)	(0.047)	(0.595)	(0.439)	(0.813)	(0.557)
NGO entry*Post-survey		-0.067		2.389**		0.384
		(0.067)		(0.948)		(0.814)
Observations	322	1585	204	619	204	619
R-squared	0.02	0.08	0.11	0.03	0.15	0.09
Unit of Analysis	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post-survey Dummy	No	Yes	No	Yes	No	Yes
Survey Data	Post	Pre & Post	Post	Pre & Post	Post	Pre & Post
Number of villages	26	57	26	54	26	54
Dep. Var. Mean in control	0.35	0.43	6.9	6.8	3.8	3.4

Note: The sample consists of children reported sick in malaria in the last month. The sample in columns 1, 3, and 5 contains endline survey data, from villages with drug shops at baseline. Columns 2, 4, and 6 add baseline data from villages with drug shops at baseline. The dependent variables are: in columns 1-2, a dummy indicating whether the child was treated with ACT, and zero if treated with non-ACT antimalarial; the number of pills that were acquired for treatment from any source (columns 3-4) or from private drug shops (columns 5-6), conditional on treatment with ACT. The control variables are: number of drug shops at baseline, number of households at baseline, and share of baseline households that believe ACT are highly effective. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.

Table A.1. Effects of NGO Entry: Beliefs about Efficacy of Malaria Medicines

Dependent Variable:	Believes ACT is highly effective, dummy		Believes non-ACT drugs are highly effective, dummy	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
NGO entry	0.011	0.007	0.013	0.040
	(0.016)	(0.015)	(0.034)	(0.032)
Observations	653	653	646	646
R-squared	0.02	0.02	0.01	0.04
Unit of Analysis	HH	HH	HH	HH
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline
Number of villages	26	26	26	26
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Dep. Var. Mean, Control	0.94	0.94	0.85	0.85

Note: Data from the endline household survey conducted in 48 randomly sampled villages (column 1 and 3), or the subset of villages that had shops at baseline (column 2 and 4). *T*he dependent variable captures whether 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 3-4 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 tables 3-8. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.