Can Competition Reduce Lemons? A Randomized Intervention in the Antimalarial Medicine Market in Uganda*

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Abstract

Markets for medicines in developing countries are known to be plagued by counterfeit and substandard products: fake drugs, in short. Examining the market for antimalarial medicine in Uganda, we study whether competition affects the prevalence of fake drugs. Specifically, we randomly assigned entry by a retailer (an NGO) providing a superior product - an authentic drug sold below prevailing market price - and investigate the response by incumbent firms and consumers. We explore 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 entry had economically important effects on quality: Approximately a year after the new market actor entered the share of incumbent firms selling fake drugs dropped by more than 50% in the intervention markets compared to the control markets. The quality improvements were accompanied by lower prices, greater market size, and better reputation among incumbents.

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1 Introduction

Malaria constitutes one of the major health problems in Africa, despite the existance of effective prevention methods and curative medicines such as artemisinin-based combination therapy (ACT).\(^1\) While the reason for this public health failure is multifaceted, recent evidence from retail markets for antimalarial drugs suggest that poor quality of medicines contributes. Understanding the determinants of drug quality in this market is therefore important from a public health perspective.\(^2\)

Beyond these concerns, studying the market for antimalarial medicine is also interesting for understanding the theory of markets and product quality: Antimalarial medicine is an experience good, where quality is unknown to the consumer prior to consumption, and difficult to infer after consumption. While the health experience after consumption may provide information about the quality of the product, inference is noisy. What compounds the inference problem is that when the underlying disease is not perfectly known to the consumer feeling ill - which is the typical case in most of sub-Saharan Africa where modern diagnostics are either unavailable or seldom used for other reasons - then even if treatment is unsuccessful one cannot confidently conclude that the drug must have been fake, because the consumer may not have had malaria in the first place.\(^3\) It is clear that standard forces for reputation building among firms are relatively weak in such a context, as one can get away with selling poor quality medicines without suffering much in terms of reputation. What is less clear, however, is what may move the market out of this bad equilibrium.

To our knowledge, we are the first to provide experimental evidence on the determinants of drug quality among firms in a developing country context.\(^4\) We collaborated

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\(^1\) 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).

\(^3\) Symptomatic diagnosis (whether the individual has fever or not) rather than parasite-based diagnostic testing is the norm in most of Africa. Misdiagnosis is therefore common. 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. Misdiagnosis, in turn, is likely to hamper learning about both the effectiveness of ACTs and their quality (Adhvaryu, 2014).

\(^4\) The closest paper is by Bennett and Yin (2015), which uses non-experimental data 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
with an NGO, Living Goods, that entered local markets (villages) where local saleswomen were selling antimalarial medicines (ACTs), among other products. They were highly competitive as their products were superior on both the quality and price dimension: the ACTs were authentic - and thus of the highest possible quality - and they were aggressively priced at point below prevailing market prices (typically 20-30 percent below).\(^5\) We collected data on drug quality and prices among incumbent firms using mystery shoppers slightly less than one year after the saleswomen had entered villages, followed by established methods (Raman Spectroscopy) to measure whether ingredients were lacking compared to what authentic drugs should contain. We combine this with household surveys to measure responses on the demand side, including quantities demanded and the reputation of local drug shops.

To fix ideas and guide the empirical analysis, we start by presenting a simple conceptual framework model. In markets for experience 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 such as the NGO can affect the market equilibrium in two ways: (i) exit of the retailers selling the lowest quality; and (ii) endogenously higher quality of drugs by the remaining retailers in order to remain competitive.

We then present evidence estimating the reduced form effects of the entry on the quality of drugs sold by incumbent sellers. 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.\(^6\) Imposing some 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 effect.

To further assess the mechanisms we use household survey data to examine how households’ beliefs about quality changed in response to the entry, and the improved market quality that followed. Consistent with the actual reduction in fake drugs, we find that households in intervention villages were 19% less likely to believe that incumbent-quality appears to be higher.

\(^5\)The saleswomen were selling a basket of goods, including other health products (e.g., pain killers, oral rehydration therapy, etc.). While this approach may have been important for the sustainability of the business model, and for what the potential health impact could be, it is unlikely that these other products had a first-order effect on the quality of antimalarial drugs studied in this paper.

\(^6\)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).
bent shops sell fake antimalarials as compared to control villages. This is consistent with reputation forces being present, where consumers had some ability to infer quality in the treatment villages. By contrast, if no inference of drug quality was possible, beliefs would have been the same across treatment and control villages. The results is also consistent with our conceptual framework, which suggests that when the NGO enters, it becomes more difficult to get away with selling fake drugs because consumers are able to compare outcomes across an entrant that always sell the highest possible quality and an incumbent who may not do so, which actually improves the ability to make inference about quality of the incumbent firm even if consumers do not know the quality of the entrant.

Finally, we show that entry of the new market actor also resulted in lower market prices among incumbents, consistent with the existence of significant ex ante mark-ups in the retail market. Evidence from our household survey data show an increase in demand so that the entry lead to greater overall market size.

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.

First, we find that consumers can identify quality improvements in the market although the learning environment is noisy. If that would not be the case there would be no pecuniary incentives to build up and maintain a high quality reputation in weakly regulated and unmonitored markets. 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.

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, 7

7 Larger firms can also exploit a number of strategies to strengthen the return to building a good reputation, including branding and advertising.
Svensson, and Yanagizawa-Drott, 2017). 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 conceptual framework 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 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.\(^8\) Because poor quality medicines can contain sub-

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\(^8\)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...
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. 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.

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

9 Amexo et al. (2004) report that over 70 percent of malaria cases in Africa are diagnosed at home.
10 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).
11 Using data from a representative sample of primary health clinics in Tanzania, Bold et al. (2011) find
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 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 (Ly-
becker, 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). Empirically, however, there is scant evidence on the relationship between quality and price in the pharmaceutical markets of developing countries. Bate et al. (2011) is an exception. Using data for several different types of drugs collected from 185 private pharmacies across 17 developing and middle-income countries, they reject the hypothesis that price is a monotone function of quality. Although drugs that fail quality tests are priced slightly lower on average, the price dispersion is so large that consumers cannot ensure the purchase of high quality through high price alone.

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

3 Conceptual Framework

To fix ideas before approaching the data, we first consider how entry by a high-quality provider may influence quality overall in the market. We focus on the quality dimension to keep things simple, and avoid complex signaling through prices. We provide a

12In Metrick and Zeckhauser (1999) and Akerlof (1970), on the other hand, equilibrium prices do not signal quality differences.

13In general, one may expect quality to be positively correlated with prices, at least when consumers have sufficient ability to infer quality based on observable characteristics or due to experience good learning dynamics. At the same time, if such mechanisms are weak, prices may not reflect quality in equilibrium.
simple model in the appendix and outline the intuition here.

**The Status Quo.** Consider a market with a continuum of identical consumers of unit mass. In the status quo case (i.e., control group) there is a single drug shop. To capture learning by consumers and reputation incentives among drug shops, let there be two time periods. In each period consumers contract fever that may either be due to malaria or some other disease. Since it is well known that in reality diagnostics are lacking in the present context, consumers do not know the exact cause of their fever, but have some prior belief that it is malaria. Yet, *ex ante* each consumer is willing to pay some price for treatment with antimalarial drugs from the local drug store, based on the prior as well as the outside option of traveling outside the village to acquire drugs.

We assume antimalarial medicine is an *experience good*, meaning that quality is not observable before purchase and difficult to infer after consumption. In addition, since there is uncertainty about whether one has malaria or some other disease causing fever, the problem is compounded such that learning about quality after treatment is a very noisy process. In particular, 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). Put differently, an unsuccessful treatment outcome may be due to low quality drugs or due to the fever not being caused by malaria in the first place. Clearly people observe their own health outcome after taking the drug but that statistic does not reveal quality in the market place due to this potential disease-treatment mismatch. Moreover, we allow for social learning such that consumers gather information from people around them who are sick and receive treatment, but even so perfect inference of quality is not possible.

Now imagine the drug store operating in the local market considers setting its quality in the first period. We allow for two types of seller types: with some probability she is an opportunistic type who simply cares about maximizing expected profits, or she is an honest type that also face some moral cost when selling fake drugs.\(^{14}\) The pecuniary trade-offs are such that that authentic drugs are more expensive for the seller, while selling fake drugs has some reputation cost in that future demand is lower since consumers have some ability to infer quality (although not perfectly). One can show that under some regularity conditions the maximization problem is convex and has an interior solution where some non-zero amounts of fake drugs are expected in the market; this amount

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\(^{14}\)This helps pin down the equilibrium but also allows us to naturally extend the model to a case where there is entry by another seller who is honest, in accordance with the intervention studied in this paper.
is increasing in the probability of having an opportunistic seller, and in the difficulty for consumers in inferring quality. The latter implication is quite intuitive since the pecuniary reputation incentives are weaker when learning about quality is noisier.

**Introducing Competition.** In constrast to the previous case, let there be two sellers in the market. To fit the empirical setting, in addition to the incumbent there is now a seller that is honest; she is committed to selling high-quality antimalarials (i.e., the NGO). The entry of a new seller committed to high quality raises a number of conceptual issues, including optimal price setting for reputation building. Again, while we recognize these may be important, to keep things parsimoneous we disregard them here and simply focus on the case where the two sellers are perceived as being identical *ex ante*; i.e., consumers believe the likelihood the incumbent and the NGO are of the honest type is the same.¹⁵

How may such entry influence the average quality set by incumbents? First, because consumers now can compare treatment and health outcomes across the two shops, the ability of consumers to infer quality improves in general. The entry of another seller means that consumers now receive two possibly correlated signals, which helps quality inference in part by ruling out that unsuccessful treatment was due to disease-treatment mismatch. Furthermore, an opportunistic seller now faces a key constraint when setting quality; too low quality might also cause consumers to buy from only the NGO in the future, as they are more likely to realize the incumbent is not an honest type selling high quality drugs. One can show that under these circumstances, *quality improvements* arise on average because those opportunistic sellers i) that maximize short term gains by setting the lowest possible quality will be forced to *exit*, as their reputation plummets leading to zero long-term demand, and ii) some mimic the NGO by *setting high quality* allowing them to remain in the market with a good reputation and positive long-term demand.

In sum, in places with higher competition due to entry, expected quality in market increases compared to the status quo, due to two possible mechanisms: extensive margin exit and intensive margin quality adjustments. The experiment, which randomly assigned where the NGO entered, will allow us to investigate these issues empirically.

It is worth pointing out that while our framework focuses on how average *quality* is affected by the NGO entry, from a consumer welfare perspective it is important to also understand impacts on *prices*. One may conjecture that incumbents that remain in the

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¹⁵In 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. Furthermore, to simplify the analysis, we assume the incumbent can observe the NGO’s type, and vice versa. This assumption can be relaxed without qualitatively affecting the key results.
market and choose to mimic the NGO in terms of quality may also choose to mimic the
NGO in terms of price, not least to be competitive. On the other hand, since providing
higher quality drugs implies incurring greater costs, to maintain some mark up, lower
prices may not be sustainable. Some firms may thus exit for this additional reason. Ulti-
mately, how prices are affected is an empirical question and we will provide evidence to
this end.

4 Design, Data, and Measurement

4.1 Design

We combine two rounds of household survey data from the pilot phase of an impact eval-
uation of a market-based community health care program in Uganda (Björkman Nyqvist,
Guariso, Svensson, and Yanagizawa-Drott, 2017) with a cross-sectional dataset on drug
quality.

For the drug quality study we use data from four districts (Bushenji, Mbale, Mbarara,
and Mpigi) characterized by high and endemic \( P. falciparum \) malaria prevalence (Figure
2). In each district, a NGO (Living Goods, or their collaborating partner BRAC) oper-
ates a market-based community health care program.\(^1\) In total, there were 99 project
villages in the four selected districts. For the experimental design, the villages were strat-
ified by location (district) and population size, thus creating matched blocks with similar
characteristics. From each block, half of the villages were then randomly assigned to the
intervention group (49 villages) and the remaining villages (50 villages) were assigned to
the control group.

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 sales-
women 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

\(^{1}\)Living Goods is an American NGO with a branch in Uganda. They operate networks of independent
entrepreneurs who sell treatment and preventive medicines, as well as other health products, mostly in
rural areas. In Uganda they work both independently and in collaboration with BRAC-Uganda. BRAC
operates a number of different programs across several developing countries with a focus on poverty alle-
viation.
were assigned. Some contamination might however 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.

4.2 Data

The trial profile is illustrated in Figure 3. A baseline household survey and a census of drug shops were implemented in all 99 project 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: 55 drug stores in 26 treatment villages and 80 drug stores in 31 control villages. 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. Of the 122 shops, 93 stores in 47 villages had ACT medicine in stock at the time of the survey. The sample of outlets with drug quality data thus consists of 93 drug stores in 47 villages, of which 57 stores are located in 27 control villages and 36 stores are located in 20 treatment villages. A follow-up household survey was conducted in the fall of 2011, approximately 18 months into the intervention, in a subset of 48 randomly selected project villages (of which 26.  

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17 The design, with 57 clusters, 2.4 drug shops per cluster, and an intra-cluster correlation coefficient of 0.2, had a 80% power to detect a 0.47 standardized effect at the 0.10 significance level. It had a 60% power to detect a standardized effect size of 0.36.  
18 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. 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. 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. 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).

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

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19To 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.

20In 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.

21The reference ACT pills used were tested and authenticated through laboratory testing by Chemiphar Laboratory (www.chemiphar.com).

22Nine 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.\textsuperscript{23}

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 vil-
lages 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 ap-
pears 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, al-
though non-ACT drugs, including Chloroquine, Quinine, and SP, are also viewed as be-

\textsuperscript{23}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. 24 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. 25

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. 26

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. 27 The prevalence is highest in the western, and most rural, districts (Bushenyi and Mbarara), and lowest in the district closest to the capital Kampala (Mpiigi). 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. 28

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

24 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.

25 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.

26 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 ACT:s. In villages with a drug store, 20 percent (or 10 percentage points) more household acquire ACT drugs from private drug shops as compared to a villages without a drug shop.

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

28 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.
If antimalarial medicine is an experience good, quality cannot be directly observed. Table 3 provides evidence to this end. 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.

Even if quality is not directly observable before purchase, but the ability to infer quality after purchase is high, then prices and quality may be correlated as the former provides a signal of the latter in equilibrium and firms can build reputation. A strand of the theoretical literature suggests that prices may or may not function as a signal of quality, depending on the context (Shapiro, 1982; Wolinsky, 1983; Milgrom and Roberts, 1986; Metrick and Zeckhauser, 1999). 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. Therefore, there is *prima facie* evidence that learning about quality is a very noisy process and antimalarial medicine is an experience good.\(^{29}\)

### 5.2 Experimental evidence

To investigate whether entry by the NGO lead to better quality in the market, 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.\(^{30}\) 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). The difference is smaller, -0.20,

---

\(^{29}\)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 actually negative; result available upon request). We do not make the distinction between the term experience good and credence good, as the definition typically differs only in the degree to which consumers can infer quality after consumption.

\(^{30}\)In the 99-villages sample, 42 villages did not have a drug shop within the village boundary at baseline.
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 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 conceptual framework outlines 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).

Estimating the relatively magnitude of these two mechanisms requires going beyond the reduced form effects. However, one can estimate upper bounds on the exit channel effect, and lower bounds on the intensive margin effect under some assumptions regarding the underlying data generating process, in particular with respect to the nature of exit. We present the results of two complementary approaches; first, we derive bounds using solely reduced form regressions; second, we impose some structure on the mechanisms and structurally estimate the bounds. As it will turn out, the evidence using either approach points to very similar conclusions and so we present the simpler exercise here, while the structural estimation is provided in the appendix.

**Extrapolating bounds from reduced form regressions.** There may be multiple reasons why outlets exit the market. However, 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 - which admittedly may be a strong assumption which we assess below as
as in our complementary approach - we can derive an upper bound on the extensive margin effect from the reduced form regressions. To see this, consider the following simple data generation process.

Let $X^D_J$ 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 $X^F_J / X_J = \mu$ 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 orthogonality conditional is arguably 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 $\delta$ of the stores randomly exit. In the treatment group, of the shops initially selling fakes an additional share $\alpha_E$ selectively exits and a share $\alpha_I$ switch from selling fake to authentic drugs, 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 $(1 - \delta - \alpha_E)\mu + (1 - \delta)(1 - \mu)$ will remain in the treatment group. Further, a share $(1 - \delta)\mu$ of the stores will sell fake drugs at the time of the drug quality survey in the control group and a share $(1 - \delta - \alpha_E - \alpha_I)\mu$ 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):

\begin{align*}
(1) & \quad y^E_{135} = \beta_0 + \beta_1 T + \epsilon \\
(2) & \quad y^I_{135} = \gamma_0 + \gamma_1 T + \epsilon
\end{align*}

then

\begin{align*}
(3) & \quad \beta_0 = (1 - \delta) \quad \beta_1 = -\alpha_E \mu \quad \gamma_0 = (1 - \delta)\mu \quad \gamma_1 = -(\alpha_E + \alpha_I)\mu
\end{align*}

\[31\] In the model, firms differ with respect to the moral cost of selling bad quality, which determines who exits. Facing competition, firms with a relatively low moral cost will sell a high share of fake drugs and thus be revealed as bad sellers and forced to exit, so that $\alpha_E$ are those firms with $\mu < \bar{\mu}$. As for $\alpha_I$, these are the firms with a medium moral cost ($\bar{\mu} < \mu < \bar{c}$) that remain in the market but increase quality to mimic the honest types. Honest firms will remain in the market and continue to sell authentic drugs. It is worth pointing out that the “moral cost” may of course capture any underlying difference in the intrinsic cost or benefit of selling fake drugs unrelated to pecuniary cost of acquiring them. In this sense, the parameter allows for a broad interpretation. We illustrate the three types of firm responses in Appendix Figure 2.
and

\[
\alpha_{E}^{\text{MAX}} = -\frac{\beta_1}{\gamma_0/\beta_0}, \quad \alpha_{I}^{\text{MIN}} = -\frac{\gamma_1 - \beta_1}{\gamma_0/\beta_0}
\]

In other words, the estimates from the two reduced form regressions provide bounds on the two mechanisms.

The relevant estimates for equation (2) are available in Table 4, Columns (4)-(6). In Table 5, we estimate the treatment effects on exit. Columns (1)-(3), which directly relate to equation (1), show that the estimates are negative but not statistically significant. Thus, we cannot reject the null hypothesis that the true effect in the “population” is zero. Columns (4)-(6) further show that there is no statistically significant effect on the likelihood that the shop is open. That said, the estimated magnitudes indicate that outlets surveyed before the intervention are approximately 7.7 percentage points less likely to be open and sell ACT at the time of the drug quality survey; the odds ratio in column (3) implies that this corresponds to a 32.4 percent lower likelihood of selling ACT. If we take these magnitudes literally, we can estimate the bounds in our sample.

In particular, using the mean of the outcome in control group in equations (1) and (2) for \( \beta_0 \) and \( \gamma_0 \), respectively, and the reduced form estimates for \( \beta_1 \) (Table 5, Column 1) and \( \gamma_1 \) (Table 4, Column 4):

\[
\beta_0 = 0.7125 \quad \beta_1 = -0.076 \quad \gamma_0 = 0.2625 \quad \gamma_1 = -0.153,
\]

then we get

\[
\alpha_{E}^{\text{MAX}} = 0.205 \quad \alpha_{I}^{\text{MIN}} = 0.209.
\]

The estimates therefore suggest that the exit channel accounts for up to 49.5% of the total effect (i.e., \( 0.205/(0.205+0.209)=0.495 \)), while the intensive margin effects accounts for at least 50.5%.

It is important to note that these estimates provide bounds because we are making the extreme assumption that any additional exit in the treatment group was only from those outlets selling fake drugs initially. Therefore, it rules out the possibility that the NGO caused some of the outlets that were selling authentic drugs to exit because they could not remain competitive in terms of price. This is arguably a strong assumption. Minor relaxations of this assumption also reinforce the conclusion that the intensive margin channel dominates. For example, if one assumes that among firms that sold authentic drugs, entry by the NGO caused 5% of them to exit, the exit channel only explains 16% of the total effect on quality while the intensive margin channel explains 84%.

\[32\text{To see this, note that equation (1) now entails } \beta_1 = -\alpha_{E} \mu - 0.05(1 - \mu), \text{ which implies } \alpha_{E}=0.12 \text{ and}\]
we conclude that the primary mechanism by which the NGO entry improved quality was by making incumbent outlets switch to better products, rather than by forcing exit of low-quality providers.

Finally, we conduct further sensitivity tests by using structural estimation acquiring bounds under various assumptions with respect to the underlying data generating process, where we allow for different types of shops to exits. The conclusion is very similar – the evidence points to the intensive margin channel accounting for the majority of the quality improvements.

5.4 Firm Reputation, Prices and Demand

Reputation of Incumbents

The entry of the NGO resulted in higher mean quality in the ACT drugs sold by private retailers. In theory, 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.

Interpreting the evidence within our simple conceptual framework, there are two complementary mechanisms that produce the result that the NGO entry affect 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 α_{i}=0.62. The extensive margin channel therefore accounts for 0.12/(0.62+0.12)=0.16.
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.\footnote{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).}

**Prices and Demand**

The experiment involved entry of a seller committed to selling authentic ACT drugs at prices below those prevailing in the local market. While it is theoretically ambiguous whether incumbents would also lower prices while simultaneously increase quality, from a consumer welfare perspective it is important to know how prices, and ultimately quantity demanded, were affected.

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 therefore 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).\footnote{No data was collected on treatment of adults.} 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.\footnote{The types of drugs used are: ACT (67 percent), Quinine (27 percent), Fansidar/SP (4 percent), and Chloroquine and other (2 percent).} 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 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).\footnote{It is worth noting that the NGO sells their products to the saleswomen at a small but positive mark-up above the wholesale cost, and that the retail price is set so that the saleswomen have a small mark-up as well. Of course, marginal profit is not the same as producer surplus, and for a complete welfare analysis one would need to include the fixed cost for the NGO.}

5.5 Alternative mechanisms and robustness

While the evidence points is consistent with increased competition by the NGO leading to higher quality and lower prices, it is worth considering potential alternative explanations.

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-ACTSs. The point estimates are close to zero and insignificant. Thus, health education does not seem to explain the findings.\textsuperscript{37}

Another potential mechanism would be that the NGO somehow informed households about the prevalence of fake drugs in the local drug stores, and/or put pressure on the drug shops directly to stop selling fake drugs. This too seems like an unlikely channel, as the NGO saleswomen, just like their customers, could not directly assess the quality of the antimalarial medicines sold by the incumbent drug stores. Perhaps more importantly, this explanation would arguably lead to worse reputation among incumbents, and not better reputation as our evidence shows. 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.

Perhaps a more critical question is whether in reality the incumbents truly know their own quality. It is possible that the sellers also face some uncertainty about the quality they purchase from wholesalers. Therefore, 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 somehow realize that they have been selling bad quality drugs as a result of the entry of the NGO, and therefore decide to switch to a different wholesaler. If these switches on average lead to switching to a better wholesaler, quality could increase. Our data does not allow us to assess wholesaler behavior. However, our conceptual framework 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 some quality. 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, be very similar to the

\textsuperscript{37}We also find no effects on knowledge and misconceptions about what causes malaria (results not included for brevity).
present conceptual framework. 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 to understand exactly how cheating or negligence occurs in the supply chain.

It is worth pointing out that since the increase in competition consisted of an entrant with both higher quality and lower price, it is unclear whether similar effects would have occurred had the NGO entered at similar prices. While we are unaware of any models on experience or credence goods that predict that below-market price entry lead to higher quality, it is plausible that the lower price, by increasing the quantity of ACTs, sped up learning about quality than would otherwise have been the case. Thus, while higher quality itself is likely not exclusively due to the lower price price, the speed at which this effect come about might be.\textsuperscript{38}

Finally, our results obviously do not speak to the question of whether improved quality or lower prices by an existing incumbent drug shop would give rise to similar effects, holding the degree of competition constant. To assess this hypothesis, one would need to conduct a different intervention than the one we evaluate. Similarly, it is an open question whether entry by a seller offering the same quality and price as the market. While this is an interesting question, obviously from an ethical perspective it would not be desirably to run such an experiment where you intentionally sell some fake drugs to people. 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.

In sum, what our results unambiguously show is that the increase in competition due to entry by the NGO, which sold a superior product, decreased the prevalence of fake drugs in competing drug shops and lower prices overall.

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,

\textsuperscript{38}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).
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 Björkman Nyqvist, Guariso, Svensson, Yanagizawa-Drott (2017) provides complementary evidence that the intervention improved health outcomes, including child mortality. While health outcomes may not be solely affected through an 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 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 (2017) 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. (2017) 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.

7 References


OECD, 2008, The Economic Impact of Counterfeiting and Piracy. OECD.


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

50 control villages → 80 drug shops (in 31 control villages) → 71 drug shops identified (29 villages) → 57 drug shops (27 villages) selling ACT

99 project villages → 55 project villages with a drug store → 55 drug shops (in 26 treatment villages) → 51 drug shops identified (25 villages) → 36 drug shops (20 villages) selling ACT

Baseline household survey (99 villages) → Baseline drug store census (99 villages) → Drug quality survey (all 55 villages with shops at baseline) → Household survey (random set of 48 out of 99 villages, of which 26 had a shop at baseline)
<table>
<thead>
<tr>
<th>Household Characteristics</th>
<th>Panel A: All Villages</th>
<th>Panel B: Villages with Drug Shops at Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.  Mean, Treatment</td>
<td>Obs. Mean, Treatment</td>
</tr>
<tr>
<td>Male head of HH has secondary education, dummy</td>
<td>2 980 0,30 0,27</td>
<td>1 817 0,32 0,29</td>
</tr>
<tr>
<td>Male head of HH has tertiary education, dummy</td>
<td>2 980 0,05 0,05</td>
<td>1 817 0,07 0,05</td>
</tr>
<tr>
<td>Radio ownership, dummy</td>
<td>2 980 0,82 0,79</td>
<td>1 817 0,85 0,82</td>
</tr>
<tr>
<td>Electricity, dummy</td>
<td>2 980 0,19 0,16</td>
<td>1 817 0,26 0,19</td>
</tr>
<tr>
<td>Thatched roof, dummy</td>
<td>2 980 0,03 0,04</td>
<td>1 817 0,02 0,04</td>
</tr>
<tr>
<td>Muslim HH, dummy</td>
<td>2 980 0,19 0,17</td>
<td>1 817 0,19 0,19</td>
</tr>
<tr>
<td>Number of u5 children in HH</td>
<td>2 980 1,72 1,75</td>
<td>1 817 1,68 1,73</td>
</tr>
<tr>
<td>Child reported sick in malaria in the last month, dummy</td>
<td>5 159 0,43 0,41</td>
<td>3 087 0,44 0,39</td>
</tr>
<tr>
<td>Sick child was treated with ACT, dummy</td>
<td>2 169 0,41 0,37</td>
<td>1 263 0,40 0,35</td>
</tr>
<tr>
<td>The ACT was bought in a drug shop, dummy</td>
<td>749 0,60 0,58</td>
<td>415 0,64 0,54</td>
</tr>
<tr>
<td># ACT pills for treating sick child, any source</td>
<td>751 6,49 6,69</td>
<td>415 6,67 6,87</td>
</tr>
<tr>
<td>Has heard of ACT, dummy</td>
<td>2 980 0,95 0,95</td>
<td>1 817 0,95 0,95</td>
</tr>
<tr>
<td>Believes ACT is highly effective, dummy</td>
<td>2 728 0,90 0,90</td>
<td>1 670 0,91 0,89</td>
</tr>
<tr>
<td>Believes non-ACT drugs are highly effective, dummy</td>
<td>2 930 0,83 0,86</td>
<td>1 785 0,86 0,85</td>
</tr>
<tr>
<td>Believes nearest drug shop sells fake drugs, dummy</td>
<td>2 841 0,28 0,26</td>
<td>1 723 0,29 0,26</td>
</tr>
<tr>
<td>Village Characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of households in the village</td>
<td>99 193,6 199,3</td>
<td>57 199,2 230,2</td>
</tr>
<tr>
<td>Number of drug shops in the village</td>
<td>99 1,12 1,60</td>
<td>57 2,12 2,58</td>
</tr>
<tr>
<td>Village has at least one drug shop</td>
<td>99 0,53 0,62</td>
<td>57 1,00 1,00</td>
</tr>
<tr>
<td>Village is a local monopoly (one drug shop)</td>
<td>99 0,27 0,26</td>
<td>57 0,50 0,42</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Drug shops selling fake drugs</th>
<th>Share of tested drugs that are fake</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>All shops</td>
<td>All shops</td>
</tr>
<tr>
<td>All districts</td>
<td>36.8% (N=57)</td>
<td>19.4% (N=346)</td>
</tr>
<tr>
<td>By district</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bushenyi</td>
<td>40.0%</td>
<td>30.0%</td>
</tr>
<tr>
<td>Mbale</td>
<td>33.3%</td>
<td>11.1%</td>
</tr>
<tr>
<td>Mbarara</td>
<td>53.3%</td>
<td>25.6%</td>
</tr>
<tr>
<td>Mpigi</td>
<td>26.1%</td>
<td>14.1%</td>
</tr>
<tr>
<td>By local competition</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Note: The sample consists of all competition</td>
<td>30.8%</td>
<td>15.9%</td>
</tr>
<tr>
<td>Competition</td>
<td>38.6%</td>
<td>20.5%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Observable Characteristics</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Share of inspectors of packages believing the sample contains fake drugs</td>
<td>Log(Price, Ush)</td>
</tr>
<tr>
<td>Drug shop sells fake drugs, dummy</td>
<td>0.134 (0.126)</td>
<td>0.004 (0.056)</td>
</tr>
<tr>
<td>Share of tested drugs that are fake</td>
<td>0.084 (0.118)</td>
<td>-0.085 (0.069)</td>
</tr>
<tr>
<td>Observations</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.61</td>
<td>0.58</td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Drug shop</td>
<td>Drug shop</td>
</tr>
<tr>
<td>Village FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Dep. Var. Mean in Control</td>
<td>0.30</td>
<td>0.30</td>
</tr>
</tbody>
</table>

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 "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

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Number of drug shops selling fake drugs in the village</th>
<th>Drug shop sells fake drugs, dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>OLS</td>
<td>OLS</td>
</tr>
<tr>
<td>NGO entry</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>NGO entry</td>
<td>-0.263**</td>
<td>-0.195*</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.106)</td>
</tr>
<tr>
<td>Observations</td>
<td>99</td>
<td>99</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.23</td>
<td>0.38</td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Village</td>
<td>Village</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Dep. Var. Mean in Control</td>
<td>0.420</td>
<td>0.420</td>
</tr>
<tr>
<td>Incidence ratio, Odds Ratio</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

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. Effects of NGO Entry on Exit

<table>
<thead>
<tr>
<th>Method</th>
<th>Drug shop is open and sells ACT, dummy</th>
<th>Drug shop has permanently or temporarily closed, dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1)</td>
<td>OLS (2)</td>
</tr>
<tr>
<td>NGO entry</td>
<td>-0.076</td>
<td>-0.077</td>
</tr>
<tr>
<td></td>
<td>(0.082)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Observations</td>
<td>135</td>
<td>135</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.059</td>
<td>0.076</td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Drug shop</td>
<td>Drug shop</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Dep. Var. Mean in Control</td>
<td>0.713</td>
<td>0.713</td>
</tr>
<tr>
<td>Odds Ratio</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Note: 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, a dummy indicating whether the shop was open and sold ACT at the time of the drug quality survey; in columns 4-6, a dummy indicating if the shop was not open at the time of the drug quality survey because it had permanently or temporarily closed. "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 measured at the village level at baseline: 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 6. Effects of NGO Entry: Consumer Beliefs About Drug Quality of Incumbent Shops

<table>
<thead>
<tr>
<th>Dummy</th>
<th>Dummy</th>
<th>Likert Scale</th>
<th>Dummy</th>
<th>Dummy</th>
<th>Dummy</th>
<th>Likert Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS</td>
<td>OLS</td>
<td>Logit</td>
<td>Ord. Logit</td>
<td>OLS</td>
<td>OLS</td>
<td>Logit</td>
</tr>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
<td>NGO entry</td>
<td>-0.065***</td>
<td>-0.065*</td>
<td>-0.304**</td>
<td>-0.286*</td>
<td>0.019</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.033)</td>
<td>(0.145)</td>
<td>(0.154)</td>
<td>(0.031)</td>
<td>(0.029)</td>
</tr>
<tr>
<td>NGO entry*Post-survey</td>
<td>-0.112***</td>
<td>-0.116**</td>
<td>-0.578**</td>
<td>-0.539**</td>
<td>(0.051)</td>
<td>(0.050)</td>
</tr>
</tbody>
</table>

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, Post Only, 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

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Log(Price, Ush)</th>
<th>Price, '000 Ush</th>
</tr>
</thead>
<tbody>
<tr>
<td>NGO entry</td>
<td>-0.146** (0.058)</td>
<td>-0.160*** (0.050)</td>
</tr>
<tr>
<td>Observations</td>
<td>93</td>
<td>93</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.53</td>
<td>0.57</td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Drug shop</td>
<td>Drug shop</td>
</tr>
<tr>
<td>District FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of villages</td>
<td>47</td>
<td>47</td>
</tr>
<tr>
<td>Dep. Var. Mean in Control</td>
<td>9.0</td>
<td>9.0</td>
</tr>
</tbody>
</table>

**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

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Treatment of children reported sick in malaria</th>
<th># ACT pills, any source</th>
<th># ACT pills, sourced from drug shops</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Treated with ACT, dummy</td>
<td># ACT pills, any source</td>
<td># ACT pills, sourced from drug shops</td>
</tr>
<tr>
<td></td>
<td>OLS</td>
<td>OLS</td>
<td>OLS</td>
</tr>
<tr>
<td>NGO entry</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>NGO entry*Post-survey</td>
<td>-0.067</td>
<td>0.057</td>
<td>1.986***</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.047)</td>
<td>(0.595)</td>
</tr>
</tbody>
</table>

| 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 |
| 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.
Online appendix
Can Competition Reduce Lemons? A Randomized Intervention in the Antimalarial Medicine Market in Uganda

1 A Simple Model of Competition and Quality

The market for fake drugs

In this appendix we provide a simple two-period model which is discussed intuitively in Section 3 in the paper. The model help shed light on incumbent sellers’ behavior in response to the entry of a seller committed to selling high quality drugs.\(^1\)

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.\(^2\)

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 the 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 in circulation (as \(s \in \mathbb{R}\)) but rather a signal on how common this is.\(^3\)

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 \(\Pi_t = 1 - c(d_t)\) is revenues

---

1The model draws on Mailath and Samuelson (2001) and Acemoglu et al. (2013).
2The 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.
3Intuitively, 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 \(s\).
minus costs in period $t$, $\delta$ 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. The second term captures the moral cost 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).\footnote{The third term also helps ensuring that the drug store’s maximization program is convex.}

Firm owners differ in their moral cost $\mu$ 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 are 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 $\theta$. 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 $\theta$.

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 ($\theta$) 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.

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 $\sigma_z^2$ 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 $\Pi_2(c - \mu) > 0$. Both assumptions are sufficient but not necessary.

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 $\mu$ and increasing in the variance of the noise term $\sigma_z^2$.

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 $d^*_2 = c - \mu$, where $0 < c - \mu < 1$ by assumption 2.

Consider then period 1. When making their first purchase consumers base their decision only on their prior ($\theta$). 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. Given the prior $\theta$, and the signal $s$, Bayesian updating gives the posterior that the incumbent seller is honest:

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

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

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

---

5When 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.
or

\[ f(s - h) \geq f(s - o). \]

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

\[ s \leq \frac{h + o}{2}. \]

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

\[ P(d_1) = \Pr (d_1 + z \leq (h + o)/2) = F \left( \frac{(h + o)/2 - d_1}{2} \right) \]

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

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

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

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

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

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

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 \( \sigma_z^2 \) is not too low, and given assumption 1, there exist an interior solution where the opportunistic sellers sell some fake drugs (see proof in Appendix B). An increase in \( \mu \) 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 \( \sigma_z^2 \), the lower the marginal return to quality.

**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.\(^6\) To simplify the analysis, we assume the incumbent can observe the NGO’s type (and vice versa).\(^7\)

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 \( s^i = d^i_1 + z^i \) and \( s^n = d^n_1 + z^n \). Both noise variables, \( z^i \) and \( z^n \), are normally distributed with mean 0 and variance \( \sigma_z^2 \).

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

\[
(8) \quad s^i \leq s^n
\]

The probability that consumers prefer to buy from the incumbent (as opposed from

---

\(^6\)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.

\(^7\)This assumption can be relaxed without qualitatively affecting the key results.
the NGO) is thus
\[ \Pr(d^i + z^i \leq z^n) = G \left( w \leq -d^i \right) \]
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

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

**Proposition 2:** With the NGO in the market, and for a sufficiently high precision of the signal \( w \) (\( \rho \) 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 \( \mu \leq \bar{\mu} \equiv c - \sqrt{\frac{2\delta(1-c)}{1-\delta}} \). 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 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.

---

\(^8\)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 \( \rho \), starting at \( \rho = 0 \), leads to higher quality.
1.1 Proof of propositions

Proposition 1: Differentiating (6) yields

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

so a sufficient condition for a maximum is that

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

Note that for a normal distribution max $|f'(s_1)|$ is $\frac{1}{\sqrt{2\pi}\sigma^2}$, so a sufficient condition for s.o.c. $< 0$ is that $\frac{1}{\sqrt{2\pi}\sigma^2} < \frac{1}{4\sigma^2} < \frac{1}{\delta \Pi(c - \mu)}$; i.e., if $\sigma^2 > \frac{\delta \Pi(c - \mu)}{4}$ 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 $\phi = \frac{\delta}{\sqrt{2\pi}\sigma^2}$ which is assumed (assumption 2).

$$\Pi_2(c - u) = \left(\frac{1}{2}(c - u)^2 - c + 1\right)$$

Applying the implicit function theorem to (6) yields

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

$$\text{s.o.c.}$$

$$\frac{\partial d}{\partial \mu} = 1 - \frac{\delta f'(-d/2)(c - \mu)}{\text{s.o.c.}}$$

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

Proposition 2: Note that $G(0) = \frac{1}{2}$ and that $\lim_{\rho \to 1} G(x)_{x \neq 0} = 0$. Thus when $\rho$ 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

$$\mu \geq \bar{\mu} \equiv c - \sqrt{\frac{2\delta}{1 - \delta \left(1 - c\right)}}$$
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 $d_1 = 0$. 
2 Structural Estimation

In Section 5.3, the orthogonality condition with respect to exit was the key identifying assumption for the reduced form bounds. To assess robustness, now instead consider a simplified and empirically based version of the conceptual framework in Section 3 and the model discussed above.

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 written as

$$q_i^* = \beta_0 + \beta_T T + v_i$$

or

$$b_i^* = \lambda_0 + \lambda_T T - v_i$$

where $T$ is a treatment indicator. Further assume firm $i$'s choice of remaining in the market can be written as

$$s_i^* = \gamma_0 + \gamma_T T + \eta_i$$

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

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

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

The two key parameters are $\gamma_T$ – capturing the effect of the entry of the NGO on the firm’s exit decision – and $\lambda_T$ – capturing the firm’s quality choice in response to the entry of the NGO. Since both effects are expected, we expect $\lambda_T < 0$ and $\gamma_T < 0$.

Equations (13) and (14) define a binary-outcome selection model with identical explanatory variables. We can identify $\lambda_T$ and $\gamma_T$ by placing restrictions on the data gen-
erating process. Specifically, 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. Appendix Figure 1 provides a simple illustration of the three types of firm responses as a function of the underlying moral cost, $\mu$. It is worth pointing out that the “moral cost” may of course capture any underlying difference in the latent cost of selling fake drugs, such as the difficulty in acquiring them. In this sense, the parameter allows for a broad interpretation. Thus, we assume that the error terms in (11) and (12) can be decomposed into two terms;

\begin{equation}
\nu_i \Rightarrow [\mu_i, \epsilon_i^q]; \eta_i \Rightarrow [\mu_i, \epsilon_i^s];
\end{equation}

and further assume that $\nu = \kappa \mu + (1 - \kappa)\epsilon^q$ and $\eta = \kappa \mu + (1 - \kappa)\epsilon^s$, where $\kappa \in [0, 1]$, and that $\mu \sim N(0, \frac{1}{\kappa}), \epsilon^q \sim N(0, \frac{1}{1-\kappa}), \epsilon^s \sim N(0, \frac{1}{1-\kappa})$, and $E [\mu \epsilon^q] = E [\mu \epsilon^s] = E [\epsilon^q \epsilon^s] = 0$, then $\eta \sim N(0, 1)$ and $\nu \sim N(0, 1)$, and $\nu$ and $\eta$ have a bivariate normal distribution with zero means, unit variances, and correlation coefficient $\rho = -\kappa$; i.e., $\rho \in [-1, 0]$. That is, by placing restrictions derived from the model on the correlation coefficient, we can estimate bounds on the parameters $\lambda_T$ and $\gamma_T$.

The model (13)-(14) can be estimated by maximum likelihood. The construction of the log-likelihood function is straightforward as the data identify only three possible events,

\begin{equation}
\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}
\end{equation}

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

$L = I (z_{i0} = 1) \Phi (-\gamma' x_i) + I (z_{i1} = 1) \Phi_2 (\gamma' x_i, \lambda' x_i, \rho) + I (z_{i2} = 1) (\Phi (-\gamma' x_i) - \Phi_2 (\gamma' x_i, \lambda' x_i, \rho))$

where $\Phi(\cdot)$ is the standard normal distribution function and $\Phi_2(\cdot, \cdot, \rho)$ is the bivariate standard normal distribution function with correlation coefficient $\rho = -\kappa$. 

10
The log-likelihood function is

\[
\ln L (\gamma, \lambda) = \sum_{z_0=1} \ln \Phi (-\gamma' x_i) + \sum_{z_1=1} \ln \left( \Phi_2 \left( \gamma' x_i, \lambda' x_i, \rho \right) \right) \\
+ \sum_{z_2=1} \ln \left( \Phi (-\gamma' x_i) - \Phi_2 \left( \gamma' x_i, \lambda' x_i, \rho \right) \right)
\]

In estimating this 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.\(^9\)

**Results**

The maximum likelihood estimates are found in Table A.2 and 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 \(\gamma_T\) and estimated intensive margin channel parameter \(\lambda_T\) are both significantly negative. Consistent with the estimates reported in Panel A, the exit channel accounts for approximately half of the total effect.\(^9\)

Panel C in Table A.2 reports the findings with \(\kappa = 0\) (or \(\rho = 0\)); that is, when the error terms in equations (11) and (12) 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.\(^10\)

Appendix Figure 2 plot the relative effects of the exit and intensive margin channel for different values of \(\kappa\) (or \(\rho\)). Intuitively, as \(\kappa\) falls (\(\rho\) 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 Appendix Figure 2, while an increase in \(\rho\), 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.

\(^9\)Sartori (2003) shows that the MLE of the binary-outcome selection model with identical explanatory variables and a given \(\rho\) is consistent and asymptotically normal provided that at least one of the independent variables are continuous without any mass points and that \(\gamma \neq \lambda\).

\(^10\)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., \(\Phi (\lambda_0 + \lambda_T T) - \Phi (\lambda_0)\).
Appendix Figure 1: Impact of entry conditional on $\mu$
Appendix Figure 2: Relative effects of the exit and intensive margin channels
Table A.1. Effects of NGO Entry: Beliefs about Efficacy of Malaria Medicines

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Believes ACT is highly effective, dummy</th>
<th>Believes non-ACT drugs are highly effective, dummy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS (1) OLS (2) OLS (3) OLS (4)</td>
<td></td>
</tr>
<tr>
<td>NGO entry</td>
<td>0.011 (0.016) 0.007 (0.015) 0.013 (0.034) 0.040 (0.032)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>653 653 646 646</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.02 HH 0.02 HH 0.01 HH 0.04 HH</td>
<td></td>
</tr>
<tr>
<td>Unit of Analysis</td>
<td>Shops at baseline Shops at baseline Shops at baseline Shops at baseline</td>
<td></td>
</tr>
<tr>
<td>Number of villages</td>
<td>26 26 26 26</td>
<td></td>
</tr>
<tr>
<td>District FE</td>
<td>Yes Yes Yes Yes</td>
<td></td>
</tr>
</tbody>
</table>
| Note: The sample consists of all shops that sold ACT at the time of the drug quality survey. The 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.
### Table A.2. Maximum likelihood estimates

<table>
<thead>
<tr>
<th>Name</th>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Bounds from reduced form linear regressions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exit effect</td>
<td>( \alpha_{E}^{\text{MAX}} )</td>
<td>0.209</td>
</tr>
<tr>
<td>—</td>
<td>(0.184)</td>
<td></td>
</tr>
<tr>
<td>Intensive margin effect</td>
<td>( \alpha_{I}^{\text{MAX}} )</td>
<td>0.249</td>
</tr>
<tr>
<td>—</td>
<td>(0.199)</td>
<td></td>
</tr>
<tr>
<td>Relative effect of the exit channel</td>
<td>( \frac{\alpha_{E}^{\text{MAX}}}{\alpha_{E}^{\text{MAX}} + \alpha_{I}^{\text{MAX}}} )</td>
<td>0.456</td>
</tr>
<tr>
<td>—</td>
<td>(0.394)</td>
<td></td>
</tr>
<tr>
<td>Relative effect of the intensive margin channel</td>
<td>( \frac{\alpha_{I}^{\text{MAX}}}{\alpha_{E}^{\text{MAX}} + \alpha_{I}^{\text{MAX}}} )</td>
<td>0.544</td>
</tr>
<tr>
<td>—</td>
<td>(0.394)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel B: Bounds from binary-outcome selection model, ( \rho(s) = -1 )</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exit effect</td>
<td>( \gamma_{T} )</td>
<td>-0.296*</td>
</tr>
<tr>
<td>—</td>
<td>(0.177)</td>
<td></td>
</tr>
<tr>
<td>Intensive margin effect</td>
<td>( \lambda_{T} )</td>
<td>-0.287*</td>
</tr>
<tr>
<td>—</td>
<td>(0.174)</td>
<td></td>
</tr>
<tr>
<td>Relative effect of the exit channel</td>
<td>( \frac{\Delta(s) + (1-\Delta(s))\Delta(b)}{(\Delta(s) + (1-\Delta(s))\Delta(b))} )</td>
<td>0.505**</td>
</tr>
<tr>
<td>—</td>
<td>(0.254)</td>
<td></td>
</tr>
<tr>
<td>Relative effect of the intensive margin channel</td>
<td>( \frac{\Delta(b)}{(\Delta(s) + (1-\Delta(s))\Delta(b))} )</td>
<td>0.495*</td>
</tr>
<tr>
<td>—</td>
<td>(0.254)</td>
<td></td>
</tr>
<tr>
<td><strong>Panel C: Bounds from binary-outcome selection model, ( \rho(s) = 0 )</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exit effect</td>
<td>( \gamma_{T} )</td>
<td>-0.239</td>
</tr>
<tr>
<td>—</td>
<td>(0.208)</td>
<td></td>
</tr>
<tr>
<td>Intensive margin effect</td>
<td>( \lambda_{T} )</td>
<td>-0.696**</td>
</tr>
<tr>
<td>—</td>
<td>(0.300)</td>
<td></td>
</tr>
<tr>
<td>Relative effect of the exit channel</td>
<td>( \frac{\Delta(s) + (1-\Delta(s))\Delta(b)}{(\Delta(s) + (1-\Delta(s))\Delta(b))} )</td>
<td>0.295</td>
</tr>
<tr>
<td>—</td>
<td>(0.215)</td>
<td></td>
</tr>
<tr>
<td>Relative effect of the intensive margin channel</td>
<td>( \frac{\Delta(b)}{(\Delta(s) + (1-\Delta(s))\Delta(b))} )</td>
<td>0.707*</td>
</tr>
<tr>
<td>—</td>
<td>(0.215)</td>
<td></td>
</tr>
</tbody>
</table>

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.