Can Good Products Drive Out Bad? A Randomized Intervention in the Antimalarial Medicine Market in Uganda*

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Abstract

How can quality be improved in markets for medicines in developing countries, which are known to be plagued by substandard and counterfeit ("fake drugs", in short) products? We study the market for antimalarial drugs in Uganda, where we randomly assign entry of a retailer (NGO) providing a superior product - an authentic drug priced below the market - and investigate how incumbent firms and consumers respond. We find that the presence of the NGO had economically important effects. Approximately one year after the new market actor entered, the share of incumbent firms selling fake drugs dropped by more than 50 % in the intervention villages, with higher quality drugs sold at significantly lower prices. Household survey evidence further shows that the quality improvements were accompanied with consumers expecting fewer fake drugs sold by drug stores. The intervention increased use of the antimalarial drugs overall. The results are consistent with a simple model where the presence of a seller committed to high quality, as opposed to an average firm, strengthens reputational incentives for competing firms to improve quality in order to not be forced out of the market, leading to 'good driving out bad'.

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1 Introduction

Malaria remains one of the major health problems in Africa, despite the existence 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 suggests that poor quality of medicines is a contributing factor.[2] Understanding the determinants of drug quality in this market is important from a public health perspective. Beyond these concerns, the market for antimalarial medicine offers a unique setting for studying the theory of markets and product quality: antimalarial medicine is an experience/credence good, in the sense that quality is unknown to the consumer prior to consumption, and may only be partially observable afterwards.[3] While the health experience after consumption may provide information about the quality of the product, inference is imperfect. What compounds the inference problem is that when the underlying disease, in this case malaria, 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 - then even if treatment is unsuccessful, one cannot confidently infer quality of the drug, because the consumer may not have had the presumed disease (malaria) in the first place. 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 suboptimal 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 with an NGO, Living Goods, that entered local markets (villages) where local saleswomen were selling antimalarial medicines (ACTs), among other products. Living Good's ACTs were highly competitive as they were superior in both quality and price: the ACTs were authentic - and thus of the highest possible quality - and were aggressively priced be-

[1] In Africa alone 174 million cases of malaria were reported in 2010 with 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 papers conducting chemical analyses of antimalarial drugs in Southeast Asia and sub-Saharan Africa, Nayyar et al. (2012) estimate that 32% of the tested samples contained too little or no active pharmaceutical ingredients, or contained an unstated drug or substance.

[3] The distinction between the term experience good and credence good typically refers to the degree to which consumers can infer quality after consumption, where for experience goods quality is revealed and for credence goods it is not.

[4] The closest paper is by Bennett and Yin (2019), 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, but in a different market where drug quality appears to be higher.

low prevailing market prices (typically 20-30 percent below).[5] We collected data on drug quality and prices among incumbent drug stores using mystery shoppers slightly less than one year after the Living Good's saleswomen had entered the villages. Following established testing methods (Raman Spectroscopy) we measured whether the drugs were authentic or not (fake), where the latter case means that the drug did not contain the ingredients that it should according to the authentic standard.[6] We combine this data with household surveys to measure responses on the demand side, including quantities demanded and the reputation of local drug stores.

To fix ideas and guide the empirical analysis, we start by presenting a simple model. In markets for goods with unknown quality before purchase, a firm's incentive to provide high-quality goods crucially hinges on consumers' ability to learn about quality after purchase (Mailath and Samuelson, 2001; Shapiro, 1982). We build our model based on such insights, but adapt it to the context of antimalarial drugs. Specifically, learning about quality based on health outcomes is hampered due to imperfect information about the underlying disease state (malarial or non-malarial, but with similar symptoms). In such a context, our model predicts, the presence of a retailer that is committed to high quality (such as an NGO) is key for improving quality in the market. Simply put, when such a seller is present, as opposed to an average firm, it is more difficult for an opportunistic, profit maximizing, competitor to get away with selling low-quality drugs because learning about quality is less noisy. This *beliefs effect* among consumers drive the new equilibrium to a higher average quality. More broadly, our model delivers a set of testable predictions on how entry of a seller committed to high quality affects the market equilibrium in terms *quality*, *exit* and *price* among incumbents, and *beliefs* about quality and *quantity* demanded among consumers.

Figure 1 provides a brief overview of the structure of the empirical investigation, showing the main outcomes that will be examined across treatment and control villages. We will first present results on the supply side, providing evidence on how incumbent drug stores responded to the NGO. We will then examine the demand side, using survey data on how households responded.[7] Approximately nine months after the new market

[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]In this paper, we use the terms 'fake' and low-quality interchangeably, meaning that a drug does not contain the ingredients that it should according to the authentic standard. Using WHO terminology, strictly speaking we are examining Substandard/Spurious/Falsely-Labelled/Falsified/Counterfeit medical products, or SSFFC drugs. We discuss definitions and measurement in detail in Section 4.

[7]Figure 1 is only meant to provide a snap shot of the empirical exercise. We will present regression tables for all outcomes, which appropriately adjusts for randomization strata (districts), clustering and includes

actor entered, the share of firms selling fake ACTs dropped by more than 50 percent in the intervention villages (Figure 1a). The model outlines two mechanisms through which this reduction could come about. When consumers have some ability to infer quality, there could be exit of drug stores selling bad quality ACTs from the market (extensive margin) or a switch from selling low quality to high quality drugs among incumbents who remain in the market (intensive margin). Which effect that will dominate depends on the degree of price undercutting by the NGO; the exit effect will be dominating only if the NGO sets price far below the market price, but otherwise the effect on quality will be driven by quality adjustments. While there was higher exit in treatment villages (Figure 1b), the coefficient is not statistically significant; a zero coefficient would imply that all of the effect is driven by quality adjustments. Thus, while both mechanisms may have been present, we do not have the power to precisely quantify their relative contribution. Finally, entry of the NGO also resulted in lower market prices among incumbents (Figure 1c), about 16 percent lower. This is broadly speaking in line with our model, which predicts that incumbents will pool on the price set by the NGO. Beyond the model, however, the evidence clearly points to the existence of not only low quality in the retail market, but also significant ex ante mark-ups most likely due to lack of competition.

We then use household survey data to examine demand responses to the intervention and the improved market conditions. According to our model, there are multiple mechanisms at play driving demand. On the one hand, there is an obvious, direct, *substitution effect* where some consumers switch to the NGO. This force reduces demand for the incumbent. On the other hand, there are counteracting forces. If the NGO undercuts the incumbent by setting a lower price, and incumbents pool on the lower price, there is a *price effect* which means that quantity demanded from incumbents increases. On top of this effect, there is the *beliefs effect* as our model predicts that consumers will expect higher quality from incumbents on average in equilibrium, which shifts the demand curve outward. The net effect of these forces on quantity demanded from incumbents is ambiguous, although overall quantity should increase. We first show that there is a counteracting force through an effect on beliefs: households in intervention villages were about 20 percent less likely to believe that incumbent stores sell fake antimalarials (Figure 1d), consistent with consumers having some ability to infer quality. If no inference of drug quality was possible, beliefs would have been the same across treatment and control villages. Moreover, we find that NGO entry increased consumption of ACT drugs acquired from all sources by about 30 percent (Figure 1e), i.e. greater market size, and there was a small but statistically insignificant increase on ACT acquired from incumbent drug stores

various results to show robustness.

(Figure 1f). This is consistent with the counteracting forces approximately canceling each other out.

These results have 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: in particular, there is little control of the quality, safety and efficacy of medicines circulating in the market (see e.g. Lancet, 2012). 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, and would be highly costly. Our findings point to several complementary approaches.

First, we find that consumers can identify quality improvements in the market even when 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. These incentives may not be strong enough for the small and informal drug stores that currently dominate the market. Our findings however, suggest that policies to facilitate the entry of larger firms, 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 products.[8]

Second, the NGO intervention we exploit in the paper is, in itself, a promising approach. Their franchised direct selling (business-in-a-bag) business has grown rapidly and is currently active in close to 1,000 villages, with a total population of 1.4 million, and continues to expand. A recently completed impact evaluation of their business program also shows promising effects, including a large reduction in under-five mortality (Björkman Nyqvist, Guariso, Svensson, and Yanagizawa-Drott, 2019). 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, are likely contributing factors. We discuss additional policy alternatives in our concluding remarks.

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

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

2 Background: The Market for Antimalarial Drugs

Below we describe some key aspects of the market antimalarial drugs in developing countries in general, as well as in Uganda in particular. We will incorporate these key factors in the stylized model we present in the next section.

Disease Burden and Diagnostics. In Africa alone, there were an estimated 200 million cases of malaria in 2017 and roughly 405,000 deaths (WHO, 2018). Children under the age of five account for the majority of the deaths. Uganda, the country in focus for this study, has the world's highest malaria incidences, with a rate of 201 cases per 1,000 individuals per year (Murray et. al., 2012). Adequately and promptly treated, malaria is a curable disease, but severe malaria can develop from seemingly uncomplicated to untreated cases within hours.[9] Artemisinin-based combination therapy (ACT) is currently recommended by the WHO as the first-line treatment of Plasmodium falciparum malaria (the most common type of malaria in sub-Saharan Africa). Multiple brands of ACTs exist, and the retail price for a dose in sub-Saharan Africa is typically around 3-8 USD.

In most of Africa, in particular, rural poorer areas, treatment of malaria is largely done at home using traditional remedies or drugs bought from local drug stores. WHO (2011a), estimates that 72 % 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.[10, 11]

In most cases, the diagnosis is made by the patient or caregiver themselves without any professional assistance or without any formal diagnostic testing (despite the WHO recommendation).[12] Symptomatic diagnosis is the norm in most of Africa which can be highly misleading since many infectious diseases mimic malaria both in initial symptoms and in signs of severe illness. That the purchase of medicine from local drugs stores does not require any formal testing together with consumer's self-diagnose expands the market for fake drugs since treatment might be ineffective either due to misdiagnosis or

[9] Getahun et. al., 2010.

[10] 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.

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

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

drug quality.[13,14]

In our model, we will take imperfect diagnosis into account since it will likely make it easier for stores to get away with selling low quality drugs.[15]

Prevalence of Low-Quality Drugs. Poor quality ACTs is a major health concern since it can obviously 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). That said, for ethical reasons obviously there are no experimental studies that vary the quality of the drug in different way to estimate the quality-health relationship in a precise way. Moreover, beyond these direct short-term effects, poor quality drugs containing sub-therapeutic levels active ingredients can also lead to the development of artemisinin resistance (WHO, 2011b), in addition to long-run adverse effects on both children and adults.[16]

ACT drugs have been viewed as a prime suspect for counterfeiting since artemisinin is significantly more expensive to produce compared to older, synthetic forms of malaria medicine.[17] A recent meta-analysis of surveys from 21 countries in sub-Saharan Africa and seven countries in Southeast Asia estimates that 32 % of tested samples failed qual-

[13]Reyburn et al. (2004), for example, find that more than half of the patients receiving treatment for malaria at government hospitals in Tanzania were not actually infected, and Cohen et al. (2015) show that only 38 percent of adults who seek treatment for malaria at drug store in Kenya actually have malaria.

[14]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).

[15]Misdiagnosis of malaria has also been shown to hamper social learning about the effectiveness of antimalarials (Adhvaryu, 2014).

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

[17]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. Decreasing costs can be achieved by using lower quality ingredients, under-dosing ingredients, cutting the processing time, or lowering hygiene controls.

ity tests and the problem is growing over time (Nayyar et. al., 2012; Newton et. al., 2011).[18] A failed quality test effectively means that the drug sample did not contain the ingredients that it should contain according to the official, authentic, standard. There are multiple underlying reasons, intentional to unintentional, that could lead to such quality deterioration along the supply chain. For this reason, the WHO has proposed the term Substandard/Spurious/Falsely-Labelled/Falsified/Counterfeit medical products (SSFFC), to capture these kinds of drugs. For simplicity, we use the term 'fake' synonymously with SSFFC and low quality.

As the term SSFFC suggests, low-quality drug at the end of the supply chain can arise in a myriad of ways, both intentionally and unintentionally. For example, the seller can buy pre-packaged counterfeit or substandard ACTs from either the counterfeiter or from wholesalers involved in the distribution of fake drugs. India, China, Nigeria and Pakistan have been listed as the main source countries for poor quality ACTs (Lybecker, 2004). Anecdotal evidence also suggests that repackaging of non-ACTs into ACT blister packages or ACT packs takes place in-country. The seller can also mix non-ACT drugs or poor-quality ACTs into ACT packages in the store. Drugs that are stored or transported under non-ideal conditions in terms of temperature or humidity may also deteriorate.

Ultimately, it is beyond the scope of this paper to pinpoint exactly how the low-quality drugs end up in the retail stores, but our model will assume that the stores have some degree of control over what quality to supply, where higher quality is sourced at higher costs.

Observability of Drug Quality. If antimalarial drugs are experience or credence goods, quality cannot be perfectly observed before purchase. In reality, even if consumers are aware of the existence of fake drugs (26 % of the households in our baseline sample report that they think the closest drug store sell fake drugs), it may be very difficult to disentangle the difference between authentic and fake ACT drugs. First, the quality of an ACT drug is difficult to distinguish based on visual characteristics alone. Figure 2 illustrates this by showing two samples of ACTs packs and blister packages purchased by our covert shopper and tested, one fake and one authentic. Systematic evidence is available in Newton et al. (2011), who 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, the authors conclude that

[18]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 packaging of counterfeit drugs is similar to that of genuine samples. We will provide evidence in the present context also pointing in this direction.

Given the evidence, describing the drugs as experience or credence goods seem appropriate, where the difference between the two is the extent to which quality can be inferred after consumption. The assumption of asymmetric information with respect to the quality provided in the drug store (as discussed above) before purchase will be a key building block of the model we present below.

The Market Structure in Uganda. The formal structure of the pharmacy and drug stores market in Uganda is similar to many countries; pharmacies and drug stores require formal licenses to purchase and distribute drugs.[19] All drugs imported and sold must be approved by the National Drug Authority (NDA) and are then included on the Essential Medicine List Uganda (EMLU). The NDA is supposed to monitor the agents in the pharmaceutical sector through inspections and quality tests of the drugs although no information is available on the passing rate for the drugs stores. Drug stores are typically small-scale businesses located in rural areas without a formal pharmacist. They purchase their medicines and health supplies from importers and distributors, wholesale and retail pharmacies, as well as from local pharmaceutical manufacturers. By law, the drug stores are restricted to a small list of medicines and health supplies but commonly, stock and sell medicines beyond what they are licensed to.

Despite the market regulations described above, private sector providers in sub-Saharan Africa are mostly unlicensed, and often diagnose illnesses incorrectly, sell truncated doses of medicines, expired drugs, and drugs not recommended by national guidelines (Buchner, 2011; Trelevan et. al., 2015). The Ugandan medical drug market is no exception and evidence shows that it is characterized by weak enforcement of laws and regulations. Private drug outlets in Uganda play a major role in selling essential medicines especially as the public health system is largely unreliable due to issues with procurement or stockouts (Economic Policy Research Centre, 2010). A study by Buchner et. al. (2019) studied the lack of enforcement to regulations in Uganda by investigating the licensing status and characteristics of large set of drugs stores in rural Uganda, finding that of the 215 drugs stores surveyed 88 percent were either unlicensed or license status was unknown to the owner. On the day of survey, 42 percent of the drug stores were closed. In terms of length of operation, 65 percent had operated for more than one year and 11 percent were newly opened (all without a license).

Our sample reveals a picture of the drug stores market in Uganda in line with the

[19] Information from the Uganda Ministry of Health and National Drug Authority.

previous literature. The private providers are also typically small and often unlicensed. 71 % of the drug stores in our control group were open on the survey day and had ACT drugs in stock, and 11 % had permanently or temporarily closed since baseline. More than 80 of drugs stores in the control areas had ACT in stock. The most common ACT medicine is Lonart which two thirds of all drug stores sold, followed by Artefan which roughly one fourth of the stores sold. A few stores sold Coartem and Lumartem. Since there are on average only 1.2 drugs stores per village, this implies that there is little variation in ACT supply within villages as well. The price per dose is roughly 4.5 USD but ranges from 3 to 8 USD. The difference in price between the different brands is only roughly 1.4 USD. The market in rural areas is characterized by relatively low competition, with 26 percent of local markets (villages) served by a local monopoly.

We further discuss the role of competition, theoretically and empirically, in what will follow.

3 Conceptual Framework

In this section we provide a stylized model which takes into account some of the key aspects of the market described in the previous section. To keep things simple, it will be a two-period model focusing on the behavior of incumbent drug stores and households in response to the entry of a seller (the NGO) committed to selling high quality drugs. The main goal is to derive predictions and insights that can be taken to the data.

3.1 The market for fake drugs

The economy is populated by consumers of antimalarial drugs, of unit mass, and a pool of sellers of antimalarial drugs. There are two periods, denoted with subscript t. We start by considering the case where there is only one seller in the market. A share μ of the sellers are honest. This type of a seller only sells high quality antimalarial drugs and sets prices to maximize profit. A share $1-\mu$ of the sellers are opportunistic. This type can also sell low quality drugs; i.e., an opportunistic type sets both prices and quality to maximize profit. The two types are denoted with superscript $T = \{H, O\}$ for honest and opportunistic types, respectively.[20]

The seller's type is not observable by the buyers (consumers). Consumers know, however, the two types' preferences.

[20]This formulation of preferences is standard in reputation models. The presence of an honest type creates incentives for the opportunistic type to build a reputation (see for example Tirole, 1996).

In each period consumers contract fever that may either be due to malaria or some other disease. Consumers do not know the exact cause of their fever as they lack the ability to diagnose the cause. There are two possible disease states: D_α and D_β, with D_α occurring with probability θ. Intuitively we can think of D_α as a disease environment where individuals either suffer from malaria or some other disease that mimics malaria in symptoms but for which individuals recover without any medical treatment, and D_β as a disease environment where individuals suffer from either malaria or some other disease that requires medical treatment (with a non-antimalarial drugs) to recover.

The quality of the antimalarial drug, q, sold by the seller can either be high, $\bar{q}$, or low, $\underline{q}$. The marginal (average) cost of selling low quality drugs is normalized to 0 and the cost of selling high quality drugs is c_H for the honest type and c for the opportunistic type, with $c \geq c_H$.[21]

The effectiveness of treatment depends on the quality of the drug and the disease state. Specifically, in disease state D_α, all consumers recover if treated with high quality antimalarial drugs, while some consumers (those not suffering from malaria) also recover if they are treated with a low quality drug (or no drug at all). In disease state D_β, some consumers (those suffering from malaria) recover if treated with high quality antimalarial drugs while no one gets well when treated with (only) low quality antimalarial medicine.

Consumers care about getting well and about the cost of treatment. However, they do not observe the quality of the drugs nor the disease state. We also assume consumers' willingness to pay for drugs varies, either because they differ in preferences or in their ability to pay. Specifically, the share of consumers willing to buy antimalarial drugs is given by

$$s_t = \max\left\{\frac{\gamma\hat{q}_t - p_t}{\gamma}, 0\right\} \tag{1}$$

where $\hat{q}_t$ is the expected quality of the drugs in period t and γ is a measure of how much consumers value quality.[22] We normalize drug quality such that $\bar{q} = 1$ and $\underline{q} = 0$. Note that these assumptions imply that all consumers would buy if $\hat{q}_t = 1$ and $p_t = 0$, and none would buy, assuming $p_t \geq 0$, if $\hat{q}_t = 0$.

[21] Normalizing the cost of selling low quality to 0 reduces the notational complexity of the analysis but has no qualitative implications.

[22] We can derive (1) from individual utility maximization in a number of ways depending on the source of the heterogeneity. For example, assume consumers differ in their ability to pay; i.e., their income varies. Assume income y^i is distributed uniformly over the unit interval. Consumers have unit demands; i.e., they buy at most one unit of the good. Each consumer i has tastes described by an (expected) conditional utility function of the form $Eu^i(p) = \frac{1}{\gamma}(\gamma\hat{q} - p)$, if she buys the drug at price p. Consumer i will buy the drug if $\gamma\hat{q} - p \geq y^i$, implying that the share of consumers that will buy is $\frac{\gamma\hat{q}-p}{\gamma}$.

In the beginning of period 1, nature draws the type of seller with the honest type chosen with probability μ. The seller then sets quality (q_1) and price (p_1) and consumers decide whether to buy antimalarial drugs given their beliefs and their prior that the seller is an honest type. At the end of the period, consumers receive a signal, z, about health outcomes. Let z' denote the outcome where "all individuals get well", z'' the outcome where "some individuals get well", and z''' the outcome where "no individual get well". Given the assumptions above we then have:

$$z = \begin{cases} z' & \text{if } \{D_\alpha \,\&\, q_1 = 1\} \\ z'' & \text{if } \{D_\beta \,\&\, q_1 = 1\} \text{ or } \{D_\alpha \,\&\, q_1 = 0\} \\ z''' & \text{if } \{D_\beta \,\&\, q_1 = 0\} \end{cases} . \tag{2}$$

In period 2, the seller again sets quality (q_2) and price (p_2), and consumers decide whether to buy antimalarial drugs given their beliefs and their posteriors that the seller is honest.

We make two assumptions:

Assumption 1: $\gamma\mu \geq c_H$ and $\gamma > 1$

Assumption 2: $\theta = \frac{1}{2}$

Assumption 1 ensures that the honest seller's markup ($p - c$) is positive. Assumption 2 is adopted to save on notation.

3.1.1 The monopoly case

We solve the problem by working backwards. The solution concept is perfect Bayesian equilibrium in pure strategies. Because honest types behave mechanistically, the focus of the analysis is on the opportunistic types.

Let h_t and o_t denote consumers' beliefs about the quality chosen by the honest and opportunistic type, respectively, in period t.

Consider period 2. When consumers make their choice of whether to buy drugs or not, they realize that only an honest type will sell high quality drugs ($q_2^H = 1$), while an opportunistic type, who does not face any reputational incentives, will set $q_2^O = 0$. Given the prior μ, Bayesian updating gives the posterior that the incumbent is honest:

$$\hat{\mu}(z|h_1, o_1) = \Pr[H|z] = \frac{\Pr[H]\Pr[z|H]}{\Pr[H]\Pr[z|H] + \Pr[O]\Pr[z|O]} . \tag{3}$$

That is

$$\hat{\mu}\left(z'|1,0\right)=1;\ \hat{\mu}\left(z''|1,0\right)=\mu;\ \hat{\mu}\left(z'''|1,0\right)=0\ , \tag{4}$$

and

$$\hat{\mu}\left(z'|1,1\right)=\mu;\ \hat{\mu}\left(z''|1,1\right)=\mu;\ \hat{\mu}\left(z'''|1,1\right)=0\,. \tag{5}$$

In the last period the honest type will sell high quality antimalarial drugs and set the price to maximize:

$$\max_{p_2} E\left[\pi_2\right]=E\left[(p_2-c_H)s_2\right]\ . \tag{6}$$

From the first order condition we can solve for the honest type's choice of price, p_2^H, and expected demand, s_2^H, as a function of expected period 2 quality, $\hat{q}_2$. That is,

$$p_2^H\left(\hat{q}_2\right)=p_2^*\left(\hat{q}_2\right)=\frac{\gamma\hat{q}_2+c_H}{2};\quad s_2^H\left(\hat{q}_2\right)=s_2^*\left(\hat{q}_2\right)=\frac{\gamma\hat{q}_2-c_H}{2\gamma}\ , \tag{7}$$

where $\hat{q}_2=\hat{\mu}h_2+\left(1-\hat{\mu}\right)o_2$, with the posteriors given in (4)-(5).

Next consider the opportunistic type. Note that an opportunistic seller will be revealed as opportunistic, and thus forced to exit, with probability 1 if $z=z'''$. The opportunistic type will also be revealed as opportunistic, given consumers' beliefs, if if sets a price that differs from that of the honest type. Consider the case when $z=z'$ or $z=z''$. Given consumers' beliefs, the opportunistic type will set $p_2^O=p_2^H$. Furthermore, as the seller has no incentive to sell high quality drugs in the last period, $q_2^O=0$.

In period 1, when making their initial purchase, consumers base their decisions only on their priors (μ). Expected period 1 quality is then simply $\hat{q}_1=\mu h_1+\left(1-\mu\right)o_1$.

The honest type again sells high quality drugs and sets price to maximize

$$\max_{p_1} E\left[\pi_1\right]=(p_1-c_H)s_1+\delta\pi_2^H\ , \tag{8}$$

where δ is the discount factor and where π_2^H is expected period 2 profit.

From the first-order condition we can again solve for the optimal price (this time as a function of period 1 expected quality), and determine expected demand, $s_1^H\left(\hat{q}_1\right)$. That is:

$$p_1^H\left(\hat{q}_1\right)=p_1^*\left(\hat{q}_1\right)=\frac{\gamma\hat{q}_1+c_H}{2};\quad s_1^H\left(\hat{q}_1\right)=s_1^*\left(\hat{q}_1\right)=\frac{\gamma\hat{q}_1-c_H}{2\gamma}\ , \tag{9}$$

where $\hat{q}_1 = 1$ if $\{h_1, o_1\} = \{1, 1\}$ and $\hat{q}_1 = \mu$ if $\{h_1, o_1\} = \{1, 0\}$.

As in period 2, the opportunistic type will mimic the honest type in terms of price setting behavior; i.e., $p_1^O = p_1^H$. Let $\pi^O\left(q_1^O, q_2^O | \{h_1, h_2\}\{o_1, o_2\}\right)$ denote total expected profit as a function of drug quality and beliefs in the two periods. There are two possible pure-strategy equilibria to consider. The opportunistic type can set low quality in both periods or high quality in period 1 and low quality in period 2.

Consider first the equilibrium in which $\{q_1^H, q_2^H\} = \{h_1, h_2\} = \{1, 1\}$ and $\{q_1^O, q_2^O\} = \{o_1, o_2\} = \{0, 0\}$. This is an equilibrium if no deviation, given beliefs, yields higher profit; i.e., if deviating and playing $q_1^O = 1$ is unprofitable and beliefs are consistent with equilibrium play. That is, if

$$\pi^O\left(0, 0 | \{1, 1\}\{0, 0\}\right) > \pi^O\left(1, 0 | \{1, 1\}\{0, 0\}\right). \tag{10}$$

Inserting the expressions for price and demand from (7) and (9), condition (10) reduces to (see online appendix for details)

$$cs_1^*(\mu) > \frac{\delta}{2} p_2^*(1)\, s_2^*(1) \quad . \tag{11}$$

The left hand side of (11) is the total (additional) cost incurred if the opportunistic seller deviates and sells high quality drugs in the first period. The right hand side of (11) is the expected discounted gain in period 2 profits from selling high quality drugs in period 1. When deviating and selling high quality in the first period, $z = z'$ with probability $1/2$ and consumers, given their beliefs, expect the (opportunistic) seller to be an honest type. Given beliefs, selling low quality in period 1 is profitable if the additional cost of selling high quality drugs in the first period outweighs the gain of higher expected discounted profits in period 2. Note that condition (11) holds if the marginal cost of supplying high quality drugs is sufficiently high; i.e., if $c > \bar{c} \equiv \frac{\delta p_2^*(1) s_2^*(1)}{2 s_1^*(\mu)}$.

Next consider the equilibrium in which $\{q_1^H, q_2^H\} = \{h_1, h_2\} = \{1, 1\}$ and $\{q_1^O, q_2^O\} = \{o_1, o_2\} = \{1, 0\}$. This is an equilibrium if deviating and playing $q_1^O = 0$ is unprofitable, given beliefs. That is, if

$$\pi^O\left(1, 0 | \{1, 1\}\{1, 0\}\right) > \pi^O\left(0, 0 | \{1, 1\}\{1, 0\}\right) \ . \tag{12}$$

Inserting the expressions for price and demand from (7) and (9), condition (12) can be written as

$$cs_1^*(1) < \frac{\delta}{2} p_2^*(\mu)\, s_2^*(\mu) \ . \tag{13}$$

The left hand side of (13) is the reduction in cost from deviating, $cs_1^H(1)$. The right hand side of (13) is the expected loss of no longer remaining in the market with certainty; deviating and selling low quality implies that, with probability $1/2$, $z = z'''$ and consumers will infer that the seller is an opportunistic type. Note that condition (13) will hold if the marginal cost, c, of supplying high quality drugs is sufficiently low; i.e., if $c < \underline{c} \equiv \frac{\delta p_2^*(\mu) s_2^*(\mu)}{2 s_1^*(1)}$. We now summarize the results presented so far.

Observation 1: (A) If $c > \bar{c}$ there *is* a unique equilibrium (perfect Bayesian equilibrium in pure strategies) in which the honest type sells high quality drugs and the opportunistic type sells low quality drugs and remains in the market with probability θ. Both types of sellers set the same price in each period. (B) If $c = c_H$, then provided that $\mu > \sqrt{\delta - \frac{1}{4}\delta^2}$, such an equilibrium continues to exist if $c_H \in \left(\frac{-4\gamma\mu+\sqrt{\Delta}}{2(\delta-4)}, \frac{-4\gamma\mu-\sqrt{\Delta}}{2(\delta-4)}\right)$, where $\Delta = 4\gamma^2\left(4\mu^2 + \delta^2 - 4\delta\right)$. (C) If $c < \underline{c}$, there exists a unique equilibrium in which both types sell high quality drugs in period 1 and the opportunistic type sells low quality drugs in period 2. In both periods the two types set the same price.

These results are intuitive. The drug stores set price, which is observable, and quality, which is not. An opportunistic type wants to be perceived as an honest type. For observable variables such as the price, the opportunistic type therefore mimics the honest type's choices. For unobservable variables such as quality, the opportunistic seller weighs the gain of mimicking the honest type - higher future expected demand - with the cost of selling high quality. If the cost is sufficiently high, the profit maximizing strategy calls for selling low quality drugs in both periods, even if there is then a risk that the seller will be revealed as opportunistic and forced to exit the market.

3.1.2 NGO in the market

Consider next the case where there are two sellers, denoted by superscript S, on the market of which one is committed to selling high-quality antimalarial drugs. That is, the second seller is assumed to be an honest type. Given the empirical setting we are considering, we label the second seller the NGO ($S = N$) and the first seller the incumbent ($S = I$).

The entry of a new seller committed to high quality raises a number of issues, including how firms compete and how beliefs about the NGO are formed.[23] We disregard most of these issues here and simply assume that the two sellers are perceived as being iden-

[23] 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 prevailing market price.

tical in period 1, that is, consumers believe the incumbent and the NGO can have either honest or opportunistic preferences. Furthermore, and again motivated by the empirical setting, we assume that consumers believe that an honest seller either set the price p^* or a price $p^N < p^*$, where p^* is the monopoly price and $p^N = p^*(1-\omega)$, with ω being the subsidy rate. We also assume the incumbent can observe the NGO's type (and vice versa).

With two sellers in the market consumers receive two signals, z^N and z^I. We assume, as seems plausible in a small village market, that the disease state is village specific, such that all consumers in the village face the same disease state (the same malaria prevalence). This assumption, given equation (2), provides the basis for the next observation.

Observation 2: If the disease state is village specific, consumers will be able to distinguish the quality choices of the two sellers if sellers choose to sell drugs of different quality.

To solve for the equilibrium, note as before that an opportunistic seller will always mimic the honest seller with respect to observable outcomes (prices). Thus, if $\hat{q}_t^I = \hat{q}_t^N = \hat{q}_t$, and the (honest) NGO sets the price p^N, the price set by the incumbent and share of consumers that buys from the incumbent are

$$p_t^I\left(\hat{q}_t\right) = (1-\omega)\, p^*\left(\hat{q}_t\right) \ , \tag{14}$$

and

$$s_t^I\left(\hat{q}_t\right) = \frac{1}{2}\frac{\gamma\hat{q}_t - (1-\omega)\, p^*\left(\hat{q}_t\right)}{\gamma} \ , \tag{15}$$

where we have assumed that the NGO and the incumbent split the demand equally when both set the same price and are perceived as selling drugs of the same expected quality. $p^*\left(\hat{q}_t\right)$ is defined in (7) and (9).

Bayesian updating, with two signals, gives the posterior, $\hat{\mu}(z^N, z^I|h_1^S, o_1^S)$, that both the incumbent and the NGO are honest types,

$$\hat{\mu}\left(z', z', |1, 0\right) = 1; \ \ \hat{\mu}\left(z'', z''|1, 0\right) = \tilde{\mu}; \ \ \hat{\mu}\left(z', z'|1, 1\right) = \hat{\mu}\left(z'', z''|1, 1\right) = \tilde{\mu} \ ,$$

where $h_t^I = h_t^N$ and $o_t^I = o_t^N$ by the assumed symmetry, and where $\tilde{\mu} \equiv \frac{\mu^2}{\mu^2+(1-\mu)^2}$. Note from observation 2 that the types are fully revealed if $q_1^I \neq q_2^N$, since then $z^I \neq z^N$.

Let $\pi^I\left(q_1^I, q_2^I|\left\{h_1^S, h_2^S\right\}\left\{o_1^S, o_2^S\right\}\right)$ denote total expected profit as a function of drug quality and beliefs in the two periods. With the (honest) NGO on the market, and with correlated signals, an opportunistic incumbent's quality choice depends on the gain (profit) of remaining in the market in the next period, which now only occurs if $q_1^I = 1$, relative to

the short run costs of selling high quality drugs in the first period. That is, mimicking the NGO in the first period is an equilibrium if,

$$\pi^I\left(1,0|\left\{1,1\right\}\left\{1,0\right\}\right) > \pi^I\left(0,0|\left\{1,1\right\}\left\{1,0\right\}\right) \ , \tag{16}$$

which, by substituting (14) and (15) into (16), simplifies to,

$$c < \underline{c}\left(\omega\right) \equiv \frac{\delta\left(1-\omega\right)p^*\left(\tilde{\mu}\right)s_2^I\left(\tilde{\mu}\right)}{s_1^I\left(1\right)} \ . \tag{17}$$

Maximizing short run profits by selling low quality drugs in the first period is an equilibrium if

$$\pi^I\left(0,0|\left\{1,1\right\}\left\{0,0\right\}\right) > \pi^I\left(1,0|\left\{1,1\right\}\left\{0,0\right\}\right) \ . \tag{18}$$

That is if

$$c > \bar{c}\left(\omega\right) \equiv \frac{\delta\left(1-\omega\right)\left[p^*\left(\tilde{\mu}\right)s_2^I\left(\tilde{\mu}\right)+p^*\left(1\right)s_2^I\left(1\right)\right]}{2s_1^I\left(\mu\right)} \ . \tag{19}$$

Below we summarize the results (see the online appendix for further details).

Observation 3: There exists a parameter space such that $\bar{c} < \underline{c}\left(\omega\right) < \bar{c}\left(\omega\right)$. For these parameter values, an opportunistic incumbent facing marginal cost $c \in \left(\bar{c}, \underline{c}\left(\omega\right)\right)$ sells low quality drugs in both periods and charges price p^* in the monopoly case, but sells high quality drugs in period 1 at price p^N when facing competition from an honest NGO. An opportunistic incumbent facing marginal cost $c > \bar{c}\left(\omega\right)$ sells low quality drugs in both periods at price p^* in the monopoly case, and sells low quality drugs in period 1 at price p^N and exits the market after one period when facing competition from an honest NGO.

We now summarize the main implications of the model. If the cost of providing high quality drugs is sufficiently high, the equilibrium with only one seller on the market will be characterized by low quality (Observation 1). That is, the cost of authentic drugs is a crucial determinant of whether low quality drugs are sold. Despite selling low quality drugs, sellers will attract demand since consumers cannot perfectly tell whether their subsequent health outcomes are due to high quality medicines, or because misdiagnosis. The equilibrium price is a positive function of expected quality, but firms selling low quality (type O) and high quality (type H) in the same market set the same price. With two sellers on the market, consumers' ability to learn about quality improves (Observation 2).

When facing competition from a high quality seller selling drugs at a subsidized price (Observation 3), opportunistic incumbents will either sell high quality (low cost types) or exit after the first period (high cost types). That is, the cost of acquiring authentic drugs determines how the incumbent responds to the entry of the NGO. Exit is more likely to occur the lower the price charged by the NGO. Because of lower prices and higher quality in equilibrium when the NGO enters, consumption will increase.

Empirical Predictions

The model provides testable implications based on observable outcomes: drug quality, price, quantity, exit and beliefs among consumers. In particular, across the assumed possible incumbent types, disease states and time periods, *on average* we would expect the entry of the NGO to:

1. Increase drug quality among incumbents who remain in the market
2. Decrease the price charged by incumbents who remain in the market, as they will pool on the price of the NGO
3. Induce exit by some incumbents, unless the price of the NGO is sufficiently high
4. Improve reputation among incumbents who remain in the market as households expect their drug quality to be higher
5. Increase overall market size (quantity consumed from all sources), while quantity consumed from incumbents who remain in the market may increase or decrease.

To provide nuance, a few words on the limitations of the empirical setup are worth mentioning. First, with higher quality and a lower price, the overall market size and consumer surplus increase, but there is no sharp prediction on quantity consumed from incumbents who remain in the market. In Figure 2, we provide a graphical illustration of the demand they face as the NGO enters. The reason for the ambiguous effect is that there are opposing mechanisms at play. On the one hand, there is a direct *substitution effect* where some consumers switch to the NGO, reducing demand for the incumbent. On the other hand, if the NGO undercuts the incumbent by setting a lower price both opportunistic and honest incumbents will pool on the lower price. This *price effect* means that quantity demanded increases. On top of this effect there is a *beliefs effect* since consumers will expect higher quality on average, in part due to increased ability to infer quality, which shifts the demand curve outward. The net effect of these forces is ambiguous. Second, the model suggests that the effect on incumbent exits crucially depends on the price

set by the NGO. In the data, we have no experimental variation to sharply test the third prediction as a function of price. Instead, we will capture the average effect given the price set by the NGO. It is unclear whether one should expect the exit effect to be big or small in this setting. Finally, the model suggests that the effect on quality is different if a profit maximizing (opportunistic) incumbent enters instead of an (honest) NGO. Here we again have no experimental variation to take to the data. These are important external validity questions, which we discuss in section 5.3 below.

4 Design, Data, and Measurement

4.1 Design

We combine two rounds of household survey data from the pilot phase of an impact evaluation of a market-based community health care program in Uganda (Björkman Nyqvist, Guariso, Svensson, and Yanagizawa-Drott, 2019) with a cross-sectional dataset on drug quality collected at follow-up.

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 4). In each district, an NGO (Living Goods, or their collaborating partner BRAC) operates a market-based community health care program.[24] In total, there were 99 project villages in the four selected districts. For the experimental design, the villages were stratified 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 saleswomen work under an implicit piece-rate scheme. They 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 only in the village to which

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

they were assigned. In the event that some sales were also made outside of the assigned villages, our estimates will represent a lower bound on the impact of the market entry.[25] Importantly, the NGO carried an ACT brand ("Lumartem") that was not sold in local drug stores 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 marketplace, 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 fake ACT drugs.

4.2 Data

The trial profile is illustrated in Figure 5. A baseline household survey and a census of drug stores were carried out in all 99 project villages at the beginning of 2010. The census verified the physical presence of all drug stores in the project villages but did not include a drug quality survey. 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.[26] At the end of 2010, approximately one 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.[27] Of the 122 stores, 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.

[25] In Björkman Nyqvist et. al., 2019 paper we find that 5.4% of the households in the control villages had been visited by a Living Goods saleswomen.

[26] The design, with 57 clusters, 2.4 drug stores 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.

[27] 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 local language on how to use a prepared script when approaching the outlet to procure the anti-malaria drug in an authentic manner. According to the script, the mystery shopper was buying medicine for her sick uncle.[28] The mystery 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 in Uganda for artemisinin-based combination therapy drugs.[29] Each mystery shopper used the same script for each drug purchase. The goal of having trained mystery shoppers is that the transaction would be as authentic as possible, and the purchased drugs would represent the average quality of the ACT drugs sold at the drug store.[30] This method, however, restricted the number of purchases from each drug store to one single adult dose of antimalarials, making our data cross-sectional, since multiple purchases could have made the store owner suspicious.[31] After the purchase was completed, and once out of sight of the store owner, the surveyor recorded the drug price and other information relevant to the purchase. The samples were then transferred to our testing facility in 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 (RS) through the use of 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 (purchased directly from the drug manufacturer), and if they are sufficiently similar, as given by a probabilistic algorithm, the sample passes the test and is considered authentic. In this paper we refer to drugs that do not pass the test as fake or low quality drugs.

[28] To avoid having the mystery 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.

[29] In only two cases did the outlet sell multiple brands with equivalent active ingredients and strength (if authentic). In these cases, the mystery shopper acquired the least expensive brand.

[30] However, if the drug store owner suspects the mystery shopper as being from the national drug authority, and is aware of what types of drugs he is selling, the owner would most likely provide the mystery shopper with an authentic drug. In that case, we are reporting a lower bound on the number of fake drugs in the drugs stores.

[31] It was important for this study not to make the drug store owner suspect of a random check by the drug authority (which also does happen in practice, although rarely).

The RS methodology is not able to provide us with exact information on why a drug fails the test, as it could be due to no or low dose of the active ingredient, insufficient complementary ingredients, etc. However, it is standard in the medical literature to refer to inauthentic drugs (as measured by the RS methodology) as counterfeit and they are widely recognized to be an important public health concern (Visser et. al., 2016). In 2011 the WHO proposed to refer to such drugs as Substandard/Spurious/Falsely-Labelled/Falsified/Counterfeit medical products (SSFFC); for simplicity we stick to the term fake drugs.[32]

Our testing procedure using the RS handheld device followed standard operating procedures that were provided to us during training at the TruScan headquarter. Immediately after procurement of drugs in the field, all necessary information was recorded (e.g. brand, generic, manufacturer, strength, drug form etc.), and identical reference drugs were purchased from either the National Drug Authority (NDA), the manufacturer, or from pharmacies in Kampala recommended by the NDA.[33] The reference ACT pills were authenticated through laboratory testing by Chemiphar Laboratory. 10 samples (full dose) of each reference antimalarial drug were tested in the lab. The laboratory tests confirmed the reference drugs to perfectly match the ingredients as specified by the pharmaceutical companies and the authentic pills included in the reference library were deemed authentic. Thereafter, testing of our drugs purchased in the field started and a sample of six pills from each drug store was tested, for a total of 558 pills.

An important advantage of Raman spectroscopy compared to alternative 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. Numerous medical studies confirm that the RS handheld device is a reliable tool and we rely on those references for making our case that RS authenticity is a credibly quality indicator (e.g. Bate et. al., 2011; Dégardin et. al, 2017). In this sense, we follow a standard protocol for assessing drug quality.[34] De-

[32] A drug sample in our data that failed the RS test could therefore safely be said to be a SSFFC drug, as opposed to an authentic drug.

[33] In total we had 9 types of ACT drugs purchased in field (difference by brand, strength and/or manufacturer etc.).

[34] Nine out of the ten largest pharmaceutical companies worldwide rely on Raman spectroscopy technology to authenticate inputs. Moreover, a growing number of national drug enforcement agencies use the TruScan Raman Spectrometer to test for counterfeit and substandard medicines. The Raman Spectroscopy methodology has been used and evaluated extensively in the medical litterature, specifically in the context

spite being widely used by pharmaceutical companies worldwide to authenticate inputs as well as by national drug enforcement agencies to test for counterfeit and substandard medicines, the RS method does not provide exact details of a drug sample. For example, authentic drugs may have poor quality if authentic manufacturers have inadequate quality control or if drugs have been exposed to extreme climatic conditions. However, a drug that fails the RS test due to extreme climatic conditions, will almost certainly also exhibit reduced clinical effectiveness and hence, it is reasonable to conclude that the drug is of low quality. Exactly how much clinical effectiveness is reduced is not known, most likely because it is unethical to run randomized trials with low-quality drugs at different levels of, and types of (e.g. the amount of active ingredients versus other compounds) quality. If the authentic manufacturers produce poor quality drugs because they have inadequate quality control, those poor quality drugs would most likely lead to reduced clinical effectiveness of the drugs. The RS is testing whether drugs sold in local markets deviate from the reference benchmarks. If the drug purchased in the village fails the test compared to the authentic drug, it is reasonable to claim that "quality" of the drugs purchased in the village is lower than the authentic drug whatever the reason for that quality drop is.

To measure households' beliefs about the quality of antimalarials sold by the drug stores, we asked each respondent in the household survey the question "Do you expect that the antimalarial medicines sold by the nearest drug store are fake?". A Likert scale with four categories was provided, including "no, none of them", "yes, a few of them", "yes, most of them", and "yes, all 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.[35]

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-

of quality testing of anti-malarial drugs.

[35]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.

lages while Panel B uses data from the sample of 57 villages with drug stores at baseline.

There is no systematic difference between the intervention and the control group at baseline and most differences in charactheristics are small. Thus, the random assignment of villages appears to be successful. Malaria morbidity among children under 5, here defined as share of children reported to have fallen sick with malaria in the last month, is 43 percent in the intervention group (41 percent in the control group), and 41 percent (37 percent in the control group) of these children were reported to have been treated with ACTs. Most households (60 percent in the intervention and 58 percent in the control group) buy their ACT drugs from private drug stores. ACT drugs are believed to be highly effective, although non-ACT drugs, including Chloroquine, Quinine, and SP, are also viewed as being effective by most households in both groups.[36] 28 percent of the households in the treatment group (26 percent in the control group) believe the nearest drug store sells fake antimalarial drugs and 32 percent (36 percent in the control group) 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 store, and the number of private drug stores are higher in the control group, the differences between the groups are not statistically significant. As the number of drug stores may influence the likelihood of fake drugs being sold, we include the number of drug stores in the vector of pre-intervention village-specific covariates.[37]

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 nearly all outcomes. The means are also similar to the full sample.[38]

Prevalence of fake drugs

How common are fake ACT drugs? Table 2 provides summary statistics of the prevalence of fake drugs in the control group.[39] 36.8 percent of the drug stores sell fake ACTs.[40] The prevalence is highest in the western, and most rural, districts (Bushenyi and Mbarara),

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

[37]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.

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

[39]We did not purchase drugs from local drug stores at baseline and are therefore using the control group sample at follow-up to describe prevalence of fake drugs.

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

and lowest in the district closest to the capital Kampala (Mpigi). Overall, 19.4 percent of all drugs fail the authenticity test. This number, however, includes data from stores where all the tested samples passed the test. When conditioning the sample on drug stores where at least one sample (pill) failed the authenticity test, 51.5 percent of the tested ACT drugs fail.[41]

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 before purchase

In our model antimalarial medicine quality is not known and cannot easily be inferred based on observable characteristics *before* purchase. To assess this assumption, we had ten independent surveyors (who had not taken part in any of our other data collection activities) visually inspect each sample and make an assessment of whether they believed the drugs were fake or not. They were only able to use visual characteristics (such as the color and size of the box, blister pack and pills, type of cardboard used for the box, characteristics of the text on the box and blister pack, type and presence of holograms, etc.) to make their assessment. Individual samples were sequentially presented and the inspectors' assessments were reported after each sample. To set prior beliefs in a manner consistent with the data, the inspectors were only informed of the overall share of fake drugs in the sample they were asked to assess but no other information (such as price or purchase location) was given. If visual cues reveal quality the predictive power of their assessment should be high. This was, however, not the case: the R-squared from a regression the visual assessment of quality indicates that visual assessment explains only three percent of the variation in actual quality. Thus, observability of drug quality before purchase is very low.[42]

Price-Quality Distributions

Even if quality is not directly observable before purchase, in equilibrium, prices and quality may be correlated as the former could provide a signal of the latter. A strand of the theoretical literature suggests that prices may or may not function as a signal of quality,

[41] It is plausible that our results in Table 1 provide a lower bound since the mystery shoppers were instructed 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, the ability to sell fake drugs as authentic should become easier.

[42] We only used data from control villages for this exercise, to avoid the possibility that treatment somehow improved observability of drug quality based on visual characteristics. That said, predictive power is nearly the same (with an R-square of 4%) if we include all villages, which is consistent with assumptions in the model in the sense that observing drug quality is not possible before purchase in both treatment and control villages.

depending on the context (Metrick and Zeckhauser, Milgrom and Roberts, 1986; 1999; Shapiro, 1982; Wolinsky, 1983). In our stylized model, for example, this could be true across local markets but not within (since drug stores will pool on the same price within the same market), assuming that the cost for stores to acquire high quality drugs relative to low quality drugs is constant across markets, and that disease conditions and incumbents types are drawn from the same distributions in all locations. These are obviously strong assumptions. Further, a higher cost of acquiring quality drugs leads to a higher equilibrium price in the model, all else equal. It also increases the parameter space for which it is optimal for an opportunistic type to sell low quality drugs, suggesting a negative relationship between price and quality across markets. In other words, it is somewhat unclear what to expect empirically using simple price-quality correlations in observational data.[43]

Figure 6 shows the price distributions for authentic and fake drugs across stores in the control group. It displays the variation across stores within districts in order to hold constant broad geographical factors such as transport costs and disease environments that affect price. As evident, the two price distributions strongly overlap, and using price to infer quality appears to be very noisy in this context, broadly consistent with the message of our model.[44]

5.2 Main Results: Experimental evidence

Quality

To investigate whether entry by the NGO led to better quality in the market, we start by presenting intention-to-treat (ITT) estimates using the 99-villages sample; that is, we use the sample of all experimental villages including those with no drug stores at baseline.[45] The dependent variable here is number of drug stores 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

[43]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 drug stores across 17 countries and find a negative correlation between fake drugs and price, controlling for various local factors. They conclude, however, that 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.

[44]In the cases with more than one store in a village, one may wonder what the price and quality relationship is. There is significant variation in drug quality across stores within villages, as village fixed effects alone explain only 36% of the variation in the share of fake drugs in the data. Nevertheless, one does not find a statistically significant correlation when regressing price on quality using village fixed effects. This is perhaps unsurprising, given that our model suggests there will be price pooling in such cases.

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

drug stores selling fake ACT drugs by 63% (Table 3, column 1). The difference is smaller, -0.20, when controlling for number of baseline drugs stores, village size, and a proxy of demand for ACTs. However, the difference is still quantitatively large – a 46% fall in number of stores selling fake drugs – albeit somewhat less precisely estimated (column 2).

Columns 3-4 use the core sample of 135 drugs stores identified at baseline to estimate reduced form effects from increased competition. These reduced form effects capture both changes along the extensive (exit of drug stores from the market for ACTs) and intensive (changes in behavior by outlets remaining in the ACT market) margin. The entry of the NGO resulted in a 15-17 percentage point reduction in the share of stores selling fake drugs and the point estimates are precisely estimated (columns 3-4). That is, out of all stores at baseline, more than 50% either stopped selling ACTs or switched from selling fake drugs to authentic drugs. In the online appendix we further show that the results are not sensitive to functional form choices in how we define quality sold by the drug store, as we get quantitatively very similar results regardless if we use the baseline dummy, the share of tested pills, or a dummy indicating that the majority of pills failed the quality test (see Table A.1).

Exit

Our model outlines two mechanisms through which this reduction in fake drugs sold could come about: exit of drug stores selling bad quality ACTs from the market (extensive margin) or a switch from selling low quality to high quality drugs (intensive margin). It is worth noting that these pharmacies sell a multitude of drugs and products, and so conceptually what we are interesting is whether they stop selling the relevant product (ACTs). Thus, what we are interested in is exit in a narrow sense of the product space, not whether the store ceases to exist.[46] In columns 5-6 of Table 3, we estimate the treatment effect on this type of exit. The estimates are positive but not statistically significant. Thus, we cannot reject the null hypothesis that the true effect in the "population" is zero, implying that the reduction in the share of private drug stores selling fake ACT drugs is driven solely by an intensive margin effect. That said, the estimated magnitudes indicate that outlets in the treatment group are more likely to be closed and/or less likely to sell ACTs. We can use the exit estimate to do a back-of-the-envelope calculation of the relative magnitudes of the two channels. Specifically, if the differential increase in the share of drug stores exiting was driven solely by the exit of drugs stores selling fake drugs at baseline in the treatment group, and assuming the baseline share of fake-selling stores

[46]There is also no evidence that the NGO caused drug stores to close, either temporarily or permanently.

out of the total number of stores is the same across groups, the point estimate of a 7.7 percentage point increase implies that approximately half of the treatment effect on quality (column 4, Table 3), is caused by the exit of firms selling fake drugs at baseline. Considering the standard errors, however, this back-of-the-envelope calculation is obviously only suggestive.[47]

Prices

Our model suggests that if the NGO enters with a lower price, both honest and opportunistic drug stores will pool on the lower price. Using the mystery shopper data, Table 4 shows that the entry of the NGO resulted in a fall in the average price of ACTs in incumbent drug stores by approximately 16% (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 stores and the NGO price therefore decreased from about 27% to 6%, on average. In fact, we can directly measure the absolute price difference of the store relative to the price set by the NGO, and estimate whether prices are on average closer. The estimates in columns 5-6 show that indeed prices in treatment villages are closer to the NGO's price. On average, they are about 18 percentage points closer in price. This is broadly consistent with the prediction of the model that stores will pool on the price of the NGO.

Finally, it is worth pointing out that since the intervention led to lower prices and increased quality, it also follows that local drug markets were characterized by a substantial prevalence of low quality products accompanied by considerable mark-ups, as reflected in our model.

Beliefs

In our model, reputation forces drive the new equilibrium. When the NGO enters it is more difficult to get away with selling low quality, partly because consumers have better ability to learn about the quality of the drugs sold. Table 5 provides evidence of such reputation forces, estimating effects on beliefs among households in our survey data. In columns 1-2, we exploit cross-sectional household data collected at endline to estimate the share of households that believes the nearest incumbent drug store sells fake drugs. Since the sample is relatively small (from the 57 villages with drug stores at baseline we only collected data for a random subset of 26 villages due to budgetary constraints), and so one

[47] This orthogonality condition is arguably a natural assumption to make given that the villages were randomly assign into treatment.

may worry about sampling variance giving rise to spurious results. To ensure that results are not driven by sampling variance, i.e. random pre-existing village-level differences in the outcome before the intervention arising, in columns 3-4 we add baseline data from all 57 villages and estimate effects using difference-in-differences. Regardless of the specification, we find statistically significant effects and if anything the point estimates become larger in magnitude with more controls and the addition of baseline data. Households in intervention villages were approximately 8-11 percentage points, or about 20%, less likely to believe that incumbent stores sell fake antimalarials as compared to control villages. [48] The evidence is thus consistent with our model and the role of reputation forces being an important mechanism driving the new equilibrium.

Quantity

Table 6 presents estimates of the effects on quantity using the household survey data. The data allows us to measure drug sourcing behavior for episodes for all children reported sick with malaria using either endline data alone (columns 1, 3 and 5) or in the combined baseline and endline data (columns 2, 4 and 6).[49] 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, of any quantity. 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 a full ACT dose. This is consistent with the fact that the NGO insisted that the saleswomen only sold full doses to customers. 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. Columns 5-6 further shows that the increase in ACT quantity is not driven by sourcing from incumbent drug stores.

Together, the evidence suggests that private drug stores lost market share when the NGO entered, but that their total quantity sold was not particularly affected. As the model suggests, this result is likely due to a combination of market forces. First, due to increased competition from the NGO, the inverse demand curve facing drug stores would have shifted inward (a substitution effect). Second, due to a lower price in drug stores, as Table 4 shows, there would have been movement down the inverse demand curve (a price effect). Third, expected quality of drug stores increased, as the evidence in Table 5 shows, the inverse demand curve facing drug stores would have shifted outward

[48] Results are robust to using ordered logit regression instead. Results not shown for brevity.

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

(a beliefs effect). The results in Table 6 suggest that these demand forces approximately canceled each other out. Is also important to keep in mind that while the saleswomen provided a convenient service going door-to-door, it is not a full-time activity. On average, each conducts about 10 household visits per day. Therefore, if someone is sick in malaria and desires treatment immediately, they may find it optimal to go to the drug shop even if expected quality is slightly worse and the price is slightly higher.

Finally, these results suggest that the first-order 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 store profits) decreased due to 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 stores' quality and prices).[50]

5.3 Discussion: External Validity and Alternative Interpretations

What if the NGO had sold at a different price?
In our setting the NGO sold authentic ACT drugs at a price 20-30 percent below the prevailing market price. In our experiment we could unfortunately not study whether there was a differential impact on the incumbent response depending on whether the NGO was selling authentic drugs at higher or lower prices. For that, ideally one would want to use experimental variation to test for heterogenous effects. This may be a fruitful avenue for future research.

That said, we can use our stylized model in Section 3 to discuss this counterfactual case. To illustrate the equilibrium, assume there is a large set of markets, each with an opportunistic incumbent. In each market, the incumbent draws a cost c from an uniform distribution over $[\bar{c}, c']$ with $c' > \bar{c}(0)$, and competes with an honest NGO. Appendix Figure A.1, Panel A, plots the equilibrium choices as a function of c when $\omega = 0$ while Panel B plots the equilibrium choices when $\omega > 0$; i.e., when antimalarial drugs are subsidized by the NGO. Opportunistic incumbents with relatively low costs of supplying high quality medicine, (such that $c < \underline{c}(\omega)$), will sell low quality in the monopoly case but high quality in the first period when competing with an (honest) NGO. Opportunistic incumbents with relatively high costs of supplying high quality medicine; i.e. with

[50] 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.

a $c > \bar{c}(\omega)$, will sell low quality medicine both in the monopoly case and when facing competition from an honest NGO, but will be forced to exit after one period in the second scenario.[51] Independent of cost structure, an opportunistic incumbent will set the same price as the honest NGO. A higher subsidy (higher ω) lowers the return to building a reputation (mimicking the NGO) as expected future profits fall. As a result, the threshold costs $\underline{c}(\omega)$ and $\bar{c}(\omega)$ fall, with a lower share of firms switching from selling low quality (under monopoly) to high quality (when competing with an honest NGO), and a higher share of firms exiting the market when competing with an honest NGO (Panel B). The online appendix Figure A.1., illustrates how the price set by the NGO affects how incumbents react. A lower price affects the extent to which low-quality firms exit the market instead of remaining in the market and switch to high quality, but it does not affect the overall effect on quality.

In sum, this analysis suggests that the exact price of the NGO does not have a first order effect on quality among incumbents. Rather, it influences which mechanisms drive equilibrium quality – whether the extensive or intensive margin effect dominates – in addition to the direct effects on prices and quantity demanded.

What if the entrant was not an NGO?

The NGO is a non-profit firm. Clearly, we would not necessarily expect similar effects if a regular for-profit firm decided to exogenously enter. As such, our empirical evidence cannot directly speak to external validity concerns of what would have happened in such a case. However, we can again use our stylized two-period model from Section 3 to discuss potential outcomes**.** Specifically, we can compare how the equilibrium would change if the opportunistic incumbent faces competition from either an opportunistic entrant or an honest for-profit entrant. To do so, however, we first need to determine how prices are set by profit-maximizing firms. Note, that if two honest types compete, given the assumption that honest types always sell high quality drugs, they compete only in prices. The Nash equilibrium of such a Bertrand game has both sellers setting $p = c_H$. If we assume that consumers face small search costs, the unique equilibrium has both firms setting $p = p^*$ as in the Diamond paradox **(**Diamond, 1971**)**.[52] With search costs, and with an

[51] For opportunistic types with $\underline{c}(\omega) \leq c \leq \bar{c}(\omega)$, there exists no pure strategy equilibrium.

[52] With small search costs we could, in the limit, also rationalize the assumption that the for-profit honest types set either $p = p^*$ or $p = p^N$. To see this assume an honest NGO sets $p = p^N$. Assume further that consumers expect sellers to set the same price, $p = p^N$, and start out at one store at random, observing the price in that store only. Consumer can search the other stores at some cost. Assume that cost is small such that consumers search for the price in the other store if $p > p^N$. Consider next the honest for-profit firm. Deviating and setting a price $p < p^N$ will increase demand, but only from existing consumers, and as a result profits will fall. Increasing the price will lead consumers to search for the NGO's price and, as a result, that all consumers will buy from the NGO.

honest for-profit entrant, the equilibrium is identical to that described in Observation 4 with $\omega = 0$. If the entrant is an opportunistic type, both the entrant and the incumbent will set $p = p^*$. As shown in the appendix, if $c < \underline{c}(0)$, the equilibrium has both sellers selling high quality in period 1 and low quality in period 2. If $c > \bar{c}' > \underline{c}(0)$, on the other hand, the equilibrium has both sellers selling low quality in period 1. Both sellers remain in the market in period 2 with probability θ and continue to sell low quality.

In other words, the model suggests that the fact that the NGO was an honest seller committed to authentic drugs is key for the effect on quality among incumbents, as we would not expect the same strong effect had a random profit-maximizing firm entered. The underlying reason why competition *per se* may not solve the quality problem is that quality is unobservable. As such, two competing sellers, while competing on prices, can get away by selling lower quality drugs. When both do so, the learning environment may not improve much compared to the monopoly situation; under certain conditions they can both remain in the market. While each seller has an incentive to raise quality so as to push their competitor out of the market, if the costs of selling low quality drugs (relative to high quality drugs) is sufficiently small, the profit maximizing strategy may still very well be to continue selling low quality.

Ideally, experimental or some type of quasi-experimental variation could be used to test the impact of different types of sellers. This may be a fruitful avenue for future research.

What if there is more competition to begin with?

An important question with respect to external validity is whether effects depend on pre-existing competition between incumbents. In the conceptual framework, to keep things simple and tractable we analyzed the effect of the NGO entering when there is a single incumbent in the village. By contrast, the data shows is not uncommon to have more than one incumbent. A natural question is then whether the effectiveness of the NGO is sensitive to initial market size. While the model is silent with respect to heterogenous treatment effects as a function of the number of incumbents, it may still be of interest to study heterogeneous impacts along this dimension. We present such results in appendix table A.2. Here we find no strong evidence that pre-existing competition matters for the treatment effect. The sign of the interaction effect points in the direction that the effects of entry are, if anything, smaller in villages with a single incumbent, but one cannot statistically reject that effects are the same in villages with one or multiple incumbents.[53]

[53]The model suggests that the marginal cost of acquiring high quality drugs among incumbents is a key determinant of quality. This object is likely heterogenous, but unobservable to the econometrician. Thus, one cannot empirical test how these costs influence the treatment effect. That said, anecdotal evidence

What if local markets (boundaries) are not well-defined?

In the model, the market is well-defined in the sense that the NGO competes for exactly the same customers as incumbents. In the data, we estimated the impact on incumbents where there is an NGO saleswoman going door-to-door in the same village. This seems appropriate given that the NGO saleswomen had well-defined designated catchment areas – the village – within which she was allowed to operate door-to-door. To ensure compliance, the NGO also had monitoring mechanisms in place through branch officers. Our survey data confirms that the saleswomen largely respected these boundaries, as very few households in control villages report buying medicine from the NGO saleswomen. Randomization at the village level provides a relatively straightforward econometric interpretation comparing outcomes for drug stores with and without the NGO saleswoman operating in the village of the drug store.

That said, there are a few reasons to expand the analysis beyond this simple approach. First, for any given drug store, we would naturally expect the competitive pressure of the NGO's catchment areas to be a function of distance in a continuous sense. Second, while the NGO saleswomen were restricted geographically, a competing drug store is naturally allowed to sell to any customer. Therefore, from the perspective of the drug store, there is not a strict market boundary. Third, many households are located in villages without a local drug store, yet have at least one store within reasonable walking distance. That is particularly relevant in this context as villages in the sample are located relatively near one another. In our baseline household survey data, we can measure how far away from a drug store each household is located. Households with a drug store in their village are located approximately 0.6 km from a drug store, on average. For those who do not have a drug store in the village, the average distance is about 1.5 km. Given a walking speed of about 3-4 km per hour, for a typical household in these villages it would take roughly one hour to walk back and forth to the nearest drug store. Together, it follows that the competitive pressure of the NGO as a whole for a drug store is increasing in the share of its customers that overlap with the catchment area of all NGO saleswomen, within a given distance.

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suggests that to acquire authentic drugs, instead of acquiring drugs from the nearest larger wholesaler, available in most of the larger cities, drug store owners could in principle travel to Kampala and acquire drugs directly from licensed wholesalers, importers and producers that are closely monitored by the government. Consistent with this idea, our data suggests that the relative travel distance to Kampala versus the district capital, as measured by Google Maps, is negatively correlated with drug quality in the control villages, whereas this correlation is not present in the treatment villages. These patterns in the data are broadly consistent with the stylized model in the sense that once the NGO enters, cost structure seizes to matter as opportunistic types will either start selling high quality or exit. These patterns are available in the online appendix, Figure A.3.

To complement our baseline approach, we perform regression analysis allowing for the forces above to be at play. We describe the data and variable construction in detail in the online appendix. The key difference to the baseline specification is that we define a new variable, *NGO Competition*, as the population share within some distance d of a drug store i that overlaps with catchment areas of all NGO saleswomen. In particular, we use three intervals each consisting of a 2.5 kilometers radius bandwidth: 0 - 2.5 km, 2.5 - 5 km, 5 - 7.5 km. We would expect effects to be monotonically decreasing in distance, since the customer base should be a function of walking distance for households. To maintain the exogeneity based of randomization of catchment areas, we include controls for the expected value of *NGO Competition* given that each catchment area had a 50 percent chance of being randomized to either the treatment or control group. Since we expect a high degree of spatial dependence based on the data construction, we use standard errors allowing for various spatial dependencies.

The results confirm that the effects on drug quality depend on distance, dissipating at longer distances to the NGO catchment areas. The regression results are presented in appendix table A.3 and figure A.2. The effects are negative and statistically significant up to 2.5 km, with suggestive evidence of effects up to 5 km. There is no evidence of effects beyond 5 km.

In sum, these results effectively give rise to two takeaways. First, perhaps unsurprisingly they indicate spatial relationships between the NGO, drug stores and households matter for how large the effects are. Second, and just as importantly, they provide a robustness test which confirms the basic story of the paper: nearby presence of NGO saleswomen induces higher quality drugs among incumbents in the market.

What if households have low trust in incumbents to begin with?

Another external validity concern is whether the effects of the NGO depend on what beliefs households have about drug quality of incumbents at baseline. It is somewhat ambiguous what we should expect here. On the one hand, if beliefs are consistent in equilibrium they should, in principle, reflect local conditions, including whether the incumbent is honest or opportunistic. On the other hand, if households are very skeptical about drug quality in general, perhaps due to low trust in the supply chain as a whole or the ability for the government to monitor the market and enforce the law, then distrust in drug stores may lead to distrust in the NGO as well. Put simply, distrust may be deep and go beyond local conditions. In this case, when distrust is high the NGO may be less effective in moving the market equilibrium as incumbents are less threatened by the NGO. In the appendix table A.4, we estimate heterogeneous treatment effects as a function of the share of household survey respondents in the village, at baseline, who believe that the

nearest drug store sells fake drugs. The evidence points to weaker effects of entry when distrust is high, but we cannot consistently reject the null hypothesis that effects are the same in villages with high and low distrust.

What if drug stores cannot perfectly observe their own quality?
A reasonable question in this context is whether the incumbents truly know, or can control, their own quality. In the stylized model they do, but it is possible that they also face some uncertainty about the quality they purchase from wholesalers. When the NGO enters, it could then be the case that drug stores that unknowingly sell low quality ACT medicines are pushed out of the market. The fact that the evidence points to intensive margin effects suggests that they have at least some ability to control their own quality, by for example switching wholesalers. Wholesalers can be found throughout the country, both licensed (government approved and in theory monitored) and unlicensed (rogue sellers without government monitoring). Anecdotally, there are wholesalers with better and worse reputation, and in general it is viewed as the best quality can be found by going straight to the licensed wholesalers in the capital of Kampala. The lowest reputation are the unlicensed itinerant wholesalers that pass through villages on motorbikes selling drugs to shops. We do not have data on wholesaler interactions so ultimately we cannot provide evidence on this mechanism. It is an avenue for future research.

In light of this possibility, what seems key is the ability for retailers to be able to infer quality across wholesalers. How would they do that? It seems reasonable they should be able to if they do some switching of providers from time to time. Even if they are initially completely naïve about their own quality when selling drugs acquired from a given wholesaler, if consumers complain whenever the drugs don't seem to work (even though they may be wrong sometimes because they didn't have malaria to begin with), over time they will have many data points to form beliefs about quality on. If they switch providers, and consumers don't complain as much anymore, they would infer that quality is better. At that point, they have a menu of expected wholesaler quality-price options to choose from. That is where our model comes in.

Our model could also be extended, or reinterpreted, to take this alternative mechanism into account by having wholesalers determining quality and retailers only setting prices. In this version, there would be two types of wholesalers (honest and opportunistic) that can provide retailers with drugs of some quality. 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 present model. 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 arises in the supply chain. [54]

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. Specifically, one 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. In addition to the quality improvements, price decreased, market size increased through higher demand, and the incumbents enjoyed a better reputation among households living in the village. While assessing the total welfare impact is beyond the scope of our study, the results on quality, price and quantity demanded make it clear that such entry can substantially increase consumer surplus. Moreover, a long-term follow up study by Björkman Nyqvist, Guariso, Svensson, Yanagizawa-Drott (2019) 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.

The results found in this paper provide policy implications but also point to an agenda for future research. In markets for experience goods and credence goods, reputational incentives are key for driving quality. Other approaches to improving drug quality related to decreasing consumer misconceptions and enhancing their ability to update their pri-

[54] There may be additional alternative interpretations of our main findings. In the model, the NGO indirectly improves learning by helping households sort out village-level health/disease shocks, making it more difficult for retailers to get away with selling low quality. An alternative story is that the NGO saleswomen may have educated or directly facilitated households' ability to better diagnose malaria, or improved households' ability to draw inferences about drugs after taking them. In appendix table A.5 we report treatment effects on knowledge about knowledge about antimalarial medicines, in particular whether ACTs are more effective than non-ACTs. The point estimates are close to zero and insignificant. Thus, health education does not seem to explain the findings. Another potential mechanism would be that if the NGO directly informed households about the prevalence of fake drugs in the local drug stores, households could put pressure on the drug shops directly to stop selling fake drugs. There is no anecdotal evidence that the saleswomen were involved in such activities. Finally, potentially mechanical effects arising from the NGO saleswomen selling directly to drug shops. The NGO carried the brand Lumartem, but only a trivial fraction, two percent, of the pills purchased in the drug shops in the treatment villages were of that brand.

ors about drug quality. Examples of such interventions include providing information to consumers about what fraction of fevers are actually malaria in their area, or subsidizing better diagnostics so that people become more aware of whether they actually have malaria or just fever. Another set of approaches would be to focus on directly improving drug quality at the local drug stores. For example, involving government agencies to conduct random quality assessments at drugs stores and publishing the results publicly to increase reputational cost or facilitating entry of larger firms or market chains that sell authentic drugs and thereby helping consumer learn about quality. These approaches would help strengthen incentives for higher quality. Which type of policy intervention would be most cost-effective in combating low-quality antimalarial medicines is beyond the scope of this paper but remains an important area for future work.

Finally, 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 and credence goods more broadly, such as fertilizers and seeds, gasoline, auto parts, electronics, baby food, and hygiene products (Mwakalebela, 2012; OECD, 2008; Rajput, 2012; Tentena, 2012), 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 willingness to experiment and adopt new technologies. Our study indicates that while reputational 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 as learning is very noisy for consumers. A recent study by Bai (2018) finds similar results, using experimental variation and structural estimation methods to investigate the quality of food in the watermelon market in China. The author provides evidence of reputational incentives for quality being weak; similarly, 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 clear. Thus, understanding the feasibility and cost-effectiveness of alternative interventions to improve reputation building mechanisms in these broader markets are important from a policymaking perspective, and to this end more research is needed.

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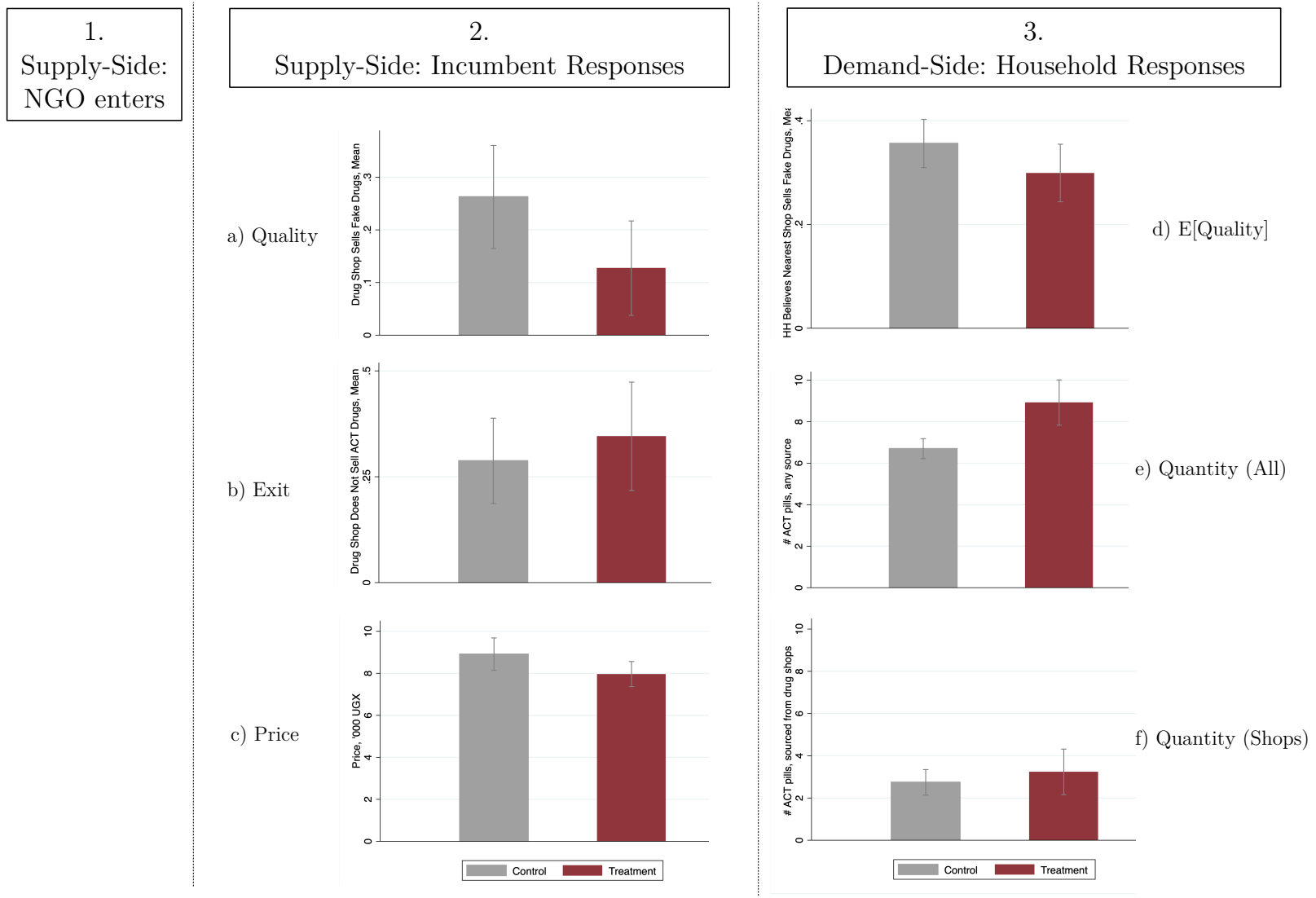
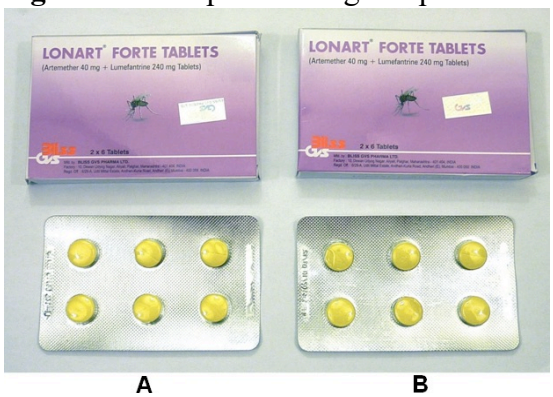
Figure 1. Structure of Empirical Investigation



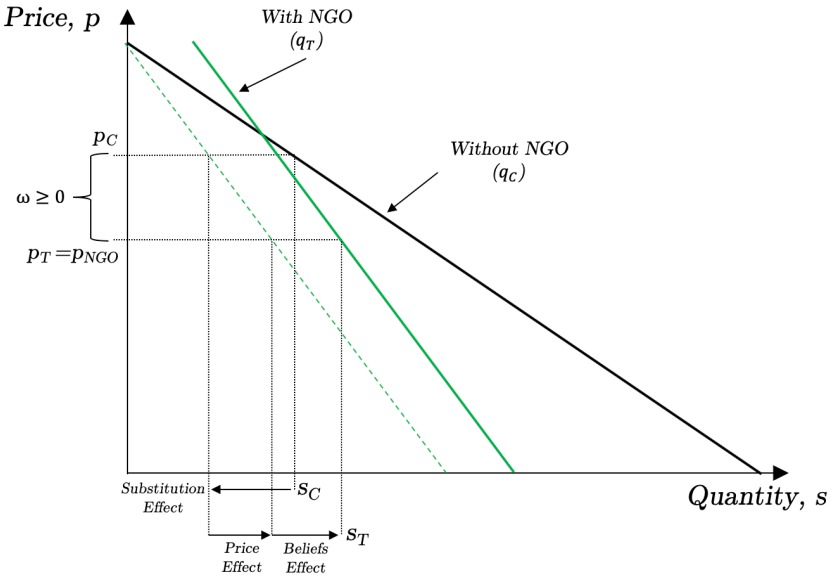
Note: The figure provides an overview of the empirical investigation. The NGO entered villages, randomly in treatment and control villages, selling authentic antimalarial drugs (ACTs) at a price below most incumbents. We first study the response by incumbent drug stores in terms of *quality* (whether the store sells fake ACT drugs), *exit* (whether the store sells ACT drugs at all) and *price*. We then examine responses among households in terms of beliefs, i.e. *expected quality* (whether the household believes the nearest drug store sells fake ACT drugs), and *quantity* demanded (number of ACT pills purchased during sickness episodes). The graphs show raw means and the associated 95 percent confidence intervals across treatment and control groups.

Figure 2. 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 3: The Effect of NGO Entry on Incumbent Demand



Note: The graph above illustrates the effects of entry of the NGO on incumbent drug stores according to the model for the case where both incumbent types (honest types who always sell high quality drugs, and opportunistic types who always profit-maximize) remain on the market in both periods; i.e. when both types set the same prices and face the same demand in both periods. Without the NGO (control group), there is an initial equilibrium of expected quality (q_C), price (p_C) and quantity (s_C). The NGO enters with a superior product (treatment group), at a higher quality and potentially a lower price ($p_{NGO} = p_C - \omega$), where ω captures the extent to which the NGO undercuts the price). The new equilibrium will be driven by three underlying mechanisms. First, there is a direct *substitution effect* where some customers purchase from the NGO instead of the incumbent. This reduces demand for the incumbents. Second, as both honest and opportunistic incumbents pool on the lower NGO price, the *price effect* implies that quantity demanded from the incumbent increases. Third, since customers' ability to infer quality improves, opportunistic incumbents that in the absence of the NGO sell low quality will now increase quality in order to remain competitive, leading to a *beliefs effect* as customers expect higher quality (q_T) from incumbents on average. This increases demand for the incumbents. Together, the expected market size (quantity of drugs consumed from both the NGO and incumbents) increases due to lower prices and higher expected quality in the market; consumer surplus also increases, but the overall effect on quantity acquired from incumbents (s_T) is ambiguous as it depends on whether the negative substitution effect dominates the positive price and beliefs effects.

Figure 4. Sample districts

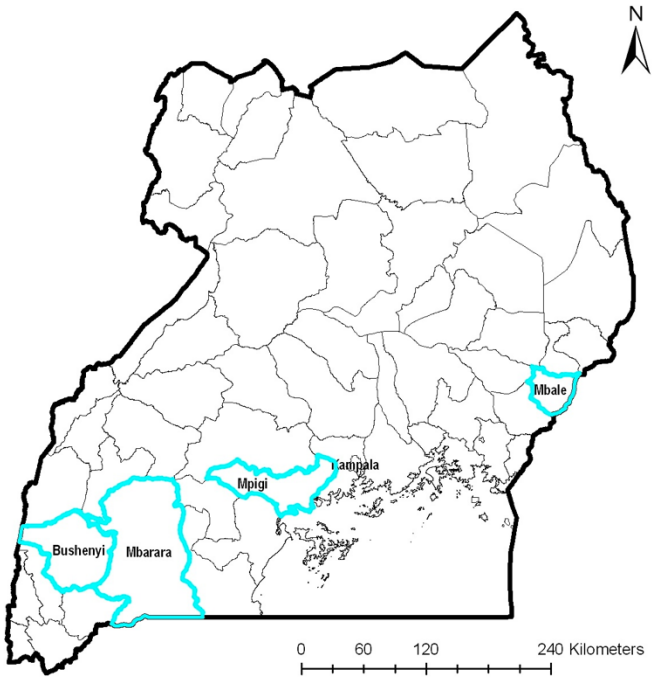


Figure 5: Trial profile

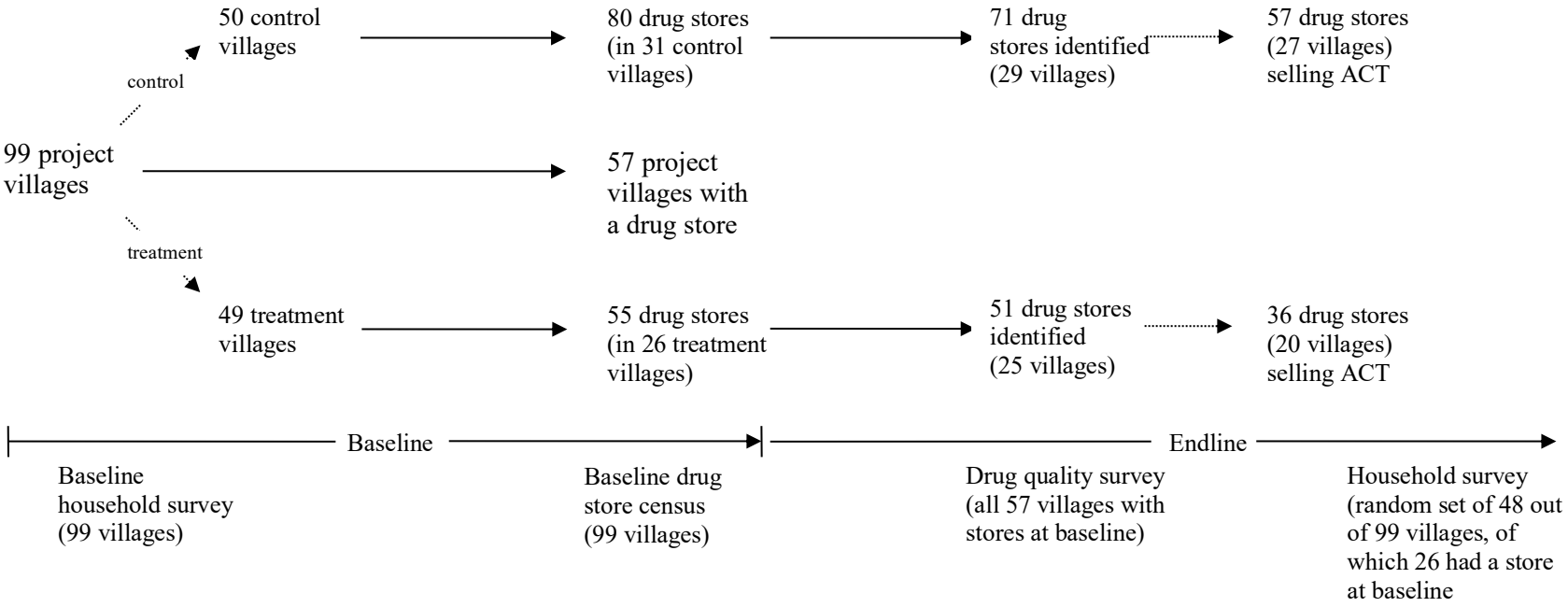
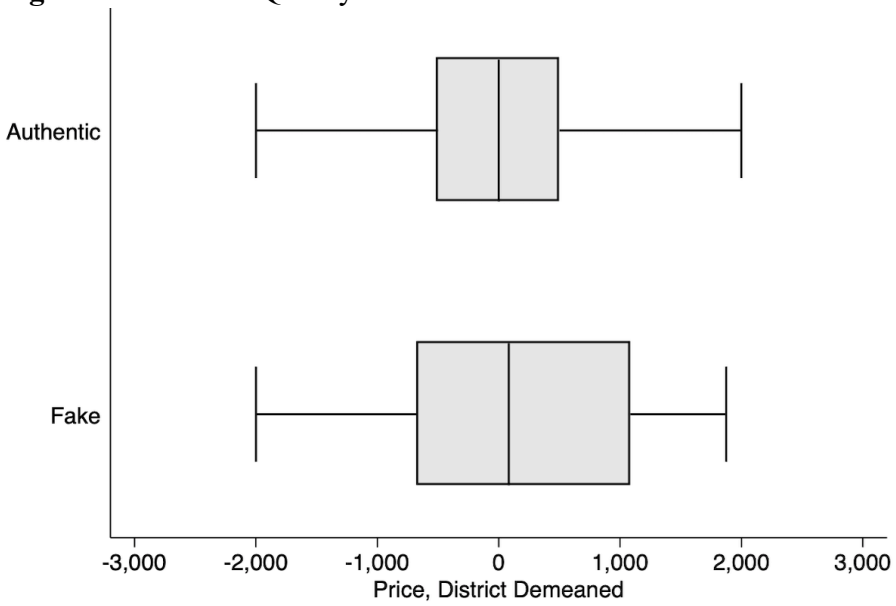


Figure 6. Price and Quality Distributions



Note: The figure shows the box plot distributions (median, 25th/75th percentile, lower/upper adjacent values) of prices, by quality, across stores within districts. The data is for the the control villages only. The graph shows that the price distributions for authentic and fake drugs are highly overlapping and that inference of quality based solely on price is noisy.

Table 1. Baseline Characteristics

	Panel A: All Villages					*Panel B: Villages with Drug Stores at Baseline*				
	Obs.	Mean, Treatment	Mean, Control	Diff.	P-value	Obs.	Mean, Treatment	Mean, Control	Diff.	P-value
Household Characteristics										
Male head of HH has secondary education, dummy	2'980	0.30	0.27	0.03	0.32	1'817	0.32	0.29	0.03	0.47
Male head of HH has tertiary education, dummy	2'980	0.05	0.05	0.00	0.74	1'817	0.07	0.05	0.03	0.06*
Radio ownership, dummy	2'980	0.82	0.79	0.04	0.17	1'817	0.85	0.82	0.03	0.33
Electricity, dummy	2'980	0.19	0.16	0.03	0.52	1'817	0.26	0.19	0.06	0.30
Thatched roof, dummy	2'967	0.03	0.04	-0.01	0.36	1'810	0.02	0.04	-0.02	0.15
Muslim HH, dummy	2'980	0.19	0.17	0.02	0.46	1'817	0.19	0.19	0.00	0.94
Number of u5 children in HH	2'980	1.72	1.75	-0.03	0.57	1'817	1.68	1.73	-0.05	0.41
Child reported sick in malaria in the last month, dummy	5'159	0.43	0.41	0.03	0.32	3'087	0.44	0.39	0.05	0.14
Sick child was treated with ACT, dummy	2'169	0.41	0.37	0.04	0.26	1'263	0.40	0.35	0.05	0.31
The ACT was bought in a drug shop, dummy	749	0.60	0.58	0.01	0.84	415	0.64	0.54	0.10	0.24
# ACT pills for treating sick child, any source	751	6.49	6.69	-0.21	0.52	415	6.67	6.87	-0.21	0.68
Has heard of ACT, dummy	2'980	0.95	0.95	0.00	0.99	1,817	0.95	0.95	0.00	0.98
Believes ACT is highly effective, dummy	2'728	0.90	0.90	0.01	0.73	1'670	0.91	0.89	0.03	0.15
Believes non-ACT drugs are highly effective, dummy	2'930	0.83	0.86	-0.04	0.26	1,785	0.86	0.85	0.01	0.88
Believes nearest drug shop sells fake drugs, dummy	2'841	0.28	0.26	0.03	0.42	1723	0.29	0.26	0.04	0.43
Village Characteristics										
Number of households in the village	99	193.6	199.3	-5.65	0.89	57	199.2	230.2	-22.8	0.68
Number of drug stores in the village	99	1.12	1.60	-0.48	0.20	57	2.12	2.58	-0.47	0.36
Village has at least one drug store	99	0.53	0.62	-0.09	0.37	57	1.00	1.00	0.00	N/A
Village is a local monopoly (one drug store)	99	0.27	0.26	0.01	0.95	57	0.50	0.42	0.08	0.55

Note: There are 99 study villages in the full sample (of which 49 are treatment villages) and 57 villages with drug stores 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. In Panel A, the p-value for the joint significance is 0.44 when the treatment dummy is regressed on all the household-level variables and the randomization stratas (districts), using village-level clustered standard errors. In Panel B, *** 1%, ** 5% , * 10% significance.

Table 2. Prevalence of Fake Antimalarial Drugs

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

Notes: The sample consists of data from the control villages with drug stores selling ACT at the time of the drug quality survey. One adult dose was purchased by covert shoppers from each store. For each store 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 stores, 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 stores selling fake drugs. Competition implies that there are more than one drug store selling ACTs in the village.

Table 3. Effects of NGO Entry: Quality

Unit of Analysis	Village		Drug shops			
Dependent Variable:	Number of drug stores selling fake drugs in the village		Drug stores sells fake drugs, dummy		Drug stores does not sell ACT drugs, dummy (exit)	
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.263**	-0.195*	-0.153**	-0.169**	0.076	0.077
	(0.118)	(0.106)	(0.072)	(0.066)	(0.082)	(0.071)
Observations	99	99	135	135	135	135
R-squared	0.23	0.38	0.08	0.10	0.059	0.076
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Dep. Var. Mean in Control	0.420	0.420	0.263	0.263	0.288	0.288

Note: In columns 1-2 the unit of analysis is a village using the sample of all 99 villages. In columns 3-6 the unit of analysis is a drug store, where the sample contains all shops identified during the baseline store census. The dependent variables are: in columns 1-2, the number of drug stores in the village that sold ACT that failed the Raman Spectroscopy authenticity tests; in columns 3-4, a dummy indicating if the drug store sold any failed drugs during the quality survey, and zero otherwise (including cases where the store was not open or did not sell ACT); in columns 5-6, a dummy indicating whether the store did not sell ACT at the time of the drug quality survey. *NGO entry* is a dummy variable equal to one if there is a door-to-door NGO distributor selling ACT drugs in the village, and zero otherwise. The control variables are: number of drug stores 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 4. Effects of NGO Entry: Price

Unit of Analysis	Drug Stores					
Dependent Variable:	Log(Price, Ush)		Price, '000 Ush		Price, % Absolute Deviation from NGO	
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.146**	-0.160***	-1.45**	-1.58***	-18.09**	-18.81**
	(0.058)	(0.050)	(0.56)	(0.50)	(7.85)	(7.66)
Observations	93	93	93	93	93	93
R-squared	0.53	0.57	0.52	0.56	0.39	0.41
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Number of villages	47	47	47	47	47	47
Dep. Var. Mean in Control	9.0	9.0	8.9	8.9	35.8	35.8

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 stores at baseline, number of households at baseline, and share of baseline households that believe ACT are highly effective. The outcome variable: in columns (1)-(4), the price for a full dose in logs and levels, respectively, and; in columns (5) and (6), the percent absolute deviation from the price set by the NGO around the time of the intervention (7000 Ugandan shillings). OLS is used in all regressions. Robust standard errors in parentheses, clustered at the village level. *** 1%, ** 5%, * 10% significance.

Table 5. Effects of NGO Entry: Consumer Beliefs

	Dependent Variable: Household believes nearest drug store sells fake drugs			
	(1)	(2)	(3)	(4)
NGO entry	-0.065**	-0.082**	0.019	0.023
	(0.028)	(0.037)	(0.031)	(0.029)
NGO entry*Post-Survey			-0.112**	-0.116**
			(0.051)	(0.050)
Observations	674	674	2397	2397
R-squared	0.01	0.01	0.04	0.05
Unit of Analysis	HH	HH	HH	HH
Survey Data	Post Only	Post Only	Pre & Post	Pre & Post
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Post-survey Dummy	No	No	Yes	Yes
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline
Number of villages	26	26	57	57
Dep. Var. Mean in Control	0.34	0.34	0.26	0.26

Note: The unit of observation is the household, restricting the sample to households in villages with drug stores at baseline to ensure that the household is referring to a drug store in the same village. The sample in columns 1-2 contains endline survey data. Columns 3-4 add baseline data from all villages with drug stores at baseline. The dependent variable is the answer to the survey question: ”Do you expect that the antimalarial medicines sold by the nearest drug store 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 stores 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: Quantity

	Treatment of children reported sick in malaria					
Dependent Variable:	Treated with ACT, dummy		# ACT pills, any source		# ACT pills, sourced from drug stores	
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.024	0.056	1.898***	-0.340	0.610	0.166
	(0.068)	(0.047)	(0.635)	(0.441)	(0.927)	(0.512)
NGO entry*Post-survey		-0.068		2.391**		0.463
		(0.067)		(0.946)		(0.811)
Observations	322	1585	204	619	204	619
R-squared	0.02	0.08	0.11	0.03	0.15	0.116
Unit of Analysis	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child	HH/Child
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Post-survey Dummy	No	Yes	No	Yes	No	Yes
Survey Data	Post	Pre & Post	Post	Pre & Post	Post	Pre & Post
Number of villages	26	57	26	54	26	54
Dep. Var. Mean in control	0.35	0.43	6.9	6.8	3.8	3.4

Note: The sample consists of children reported sick in malaria in the last month. The sample in columns 1, 3, and 5 contains endline survey data from villages with drug stores at baseline. Columns 2, 4, and 6 add baseline data from villages with drug stores 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 stores (columns 5-6), conditional on treatment with ACT. The control variables are: number of drug stores 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

1. Conceptual Framework: Details
2. Spatial Estimation
3. Figures
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Online Appendix: Can Competition Reduce Lemons? A Randomized Intervention in the Antimalarial Market in Uganda

Online Appendix 1: Conceptual Framework

Observation 1

A: The opportunistic type always sells low quality drugs

Deriving condition (11)**.**

Inserting the expressions for price and demand from (7) and (9) in (10) gives:

$$\begin{aligned} & p_1^*(\mu)\, s_1^*(\mu) + \delta \tfrac{1}{2} p_2^*(\mu)\, s_2^*(\mu) > \\ & (p_1^*(\mu) - c)\, s_1^*(\mu) + \delta \tfrac{1}{2} p_2^*(1)\, s_2^*(1) + \delta \tfrac{1}{2} p_2^*(\mu)\, s_2^*(\mu) \quad , \end{aligned} \tag{20}$$

which simplifies to

$$c > \bar{c} \equiv \frac{\delta p_2^*(1)\, s_2^*(1)}{2 s_1^*(\mu)} \tag{21}$$

as in condition (11).

B: Low quality equilibrium with identical costs

Consider the case where $c = c_H$. Then the left and right hand sides of (20) are equal if

$$(\delta - 4)\, c^2 + 4\gamma\mu c - \gamma^2 \delta = 0\,. \tag{22}$$

This quadratic equation has a maximum point since $(\delta - 4) < 0$, and two distinct roots if the discriminant (Δ) is positive; that is if

$$\Delta = 4\gamma^2 \left(4\mu^2 + \delta^2 - 4\delta\right) > 0\,. \tag{23}$$

A necessary condition for $\Delta > 0$ is thus that $4\mu^2 + \delta^2 - 4\delta > 0$; i.e. that

$$\mu > \sqrt{\delta - \tfrac{1}{4}\delta^2} \quad . \tag{24}$$

If (24) holds, then (11) holds for $c = c_H$ provided that

$$c_H \in \left[\frac{-4\gamma\mu + \sqrt{\Delta}}{2(\delta - 4)}, \frac{-4\gamma\mu - \sqrt{\Delta}}{2(\delta - 4)} \right] \quad . \tag{25}$$

C: The opportunistic type sells high quality drugs in the first period

Deriving condition (13)

Inserting the expressions for price and demand from (7) and (9) in (12) gives:

$$(p_1^*(1) - c)\, s_1^*(1) + \delta p_2^*(\mu)\, s_2^*(\mu) > p_1^*(1)\, s_1^*(1) + \delta \tfrac{1}{2} p_2^*(\mu)\, s_2^*(\mu) \quad , \tag{26}$$

which simplifies to

$$c < \underline{c} \equiv \frac{\delta p_2^*(\mu)\, s_2^*(\mu)}{2 s_1^*(1)} \, , \tag{27}$$

as in condition (13).

Observation 3

Deriving condition (17)

Substituting (14) and (15) in (16) gives:

$$((1-\omega)\, p^*(1) - c)\, s_1^I(1) + \delta(1-\omega)\, p^*(\tilde{\mu})\, s_2^I(\tilde{\mu}) > (1-\omega)\, p^*(1)\, s_1^I(1) \quad , \tag{28}$$

which simplifies to

$$c < \underline{c}(\omega) \equiv \frac{\delta(1-\omega)\, p^*(\tilde{\mu})\, s_2^I(\tilde{\mu})}{s_1^I(1)} \quad , \tag{29}$$

i.e., condition (17).

Deriving condition (19)

Substituting (14) and (15) in (18) gives:

$$\begin{aligned} &(1-\omega)\, p^*(\mu)\, s_1^I(\mu) - ((1-\omega)\, p^*(\mu) - c)\, s_1^I(\mu) \\ &-\delta \frac{1}{2} \left[(1-\omega)\, p^*(\tilde{\mu})\, s_2^I(\tilde{\mu}) + (1-\omega)\, p^*(1)\, s_2^I(1) \right] > 0 \quad , \end{aligned} \tag{30}$$

which simplifies to

$$c > \bar{c}(\omega) \equiv \frac{\delta \frac{1}{2}\left[(1-\omega)\, p^*(\tilde{\mu})\, s_2^I(\tilde{\mu}) + (1-\omega)\, p^*(1)\, s_2^I(1)\right]}{s_1^I(\mu)} \quad , \tag{31}$$

as in condition (19).

Note that $\underline{c}(\omega) \leq \bar{c}(\omega)$ as the denominator in (29) is strictly smaller than the denominator in (31), and the numerator in (31) is strictly larger than the numerator in (29) for $\mu < 1$.

Note further that $\frac{\partial}{\partial \omega}\underline{c}(\omega) < 0$ and that $\underline{c}(\omega) > \bar{c}$ (given in (21)), at least for a sufficiently small ω and a sufficiently large μ. To see this, consider the case where $\omega = 0$. Then

$$\underline{c}(0) = \frac{\delta p^*(\tilde{\mu})\, s_2^I(\tilde{\mu})}{s_1^I(1)} > \frac{\delta p_2^*(1)\, s_2^*(1)}{2 s_1^*(\mu)} = \bar{c} \quad , \tag{32}$$

which simplifies to

$$2(\gamma\tilde{\mu} + c_H)(\gamma\tilde{\mu} - c_H)(\gamma\mu - c_H) > (\gamma + c_H)(\gamma - c_H)^2 \quad , \tag{33}$$

which strictly holds when $\mu \longrightarrow 1$.

Two opportunistic types compete

Consider the case when two opportunistic types compete; i.e. $S = \{S_1, S_2\}$, where S_1 denotes seller 1 and S_2 denotes seller 2. We assume that consumers face small search costs; so the equilibrium price, when two honest types compete is $p = p^*$. The opportunistic types will mimic honest types in their price setting behavior; i.e. $p_t^s = p^*$. Consider first the equilibrium where the opportunistic sellers sell high quality in period 1 and low quality in period 2. This is an equilibrium if

$$\pi^O(1,0|\{1,1\}\{1,0\}) > \pi^O(0,0|\{1,1\}\{1,0\}) \quad . \tag{34}$$

That is, if

$$(p^*(1) - c)\, s_1^S(1) + \delta p^*(\tilde{\mu})\, s_2^S(\tilde{\mu}) > p^*(1)\, s_1^S(1) \ , \tag{35}$$

which, by substituting (14) and (15) in (34), simplifies to

$$c < c < \frac{\delta p^*(\tilde{\mu}) s_2^I(\tilde{\mu})}{s_1^I(1)} \equiv \underline{c}(0) \quad . \tag{36}$$

Maximizing short run profits by selling low quality drugs in the first period is an equilibrium if

$$\pi^O(0,0|\{1,1\}\{0,0\}) > \pi^O(1,0|\{1,1\}\{0,0\}) \ , \tag{37}$$

that is if

$$p^*(\mu) s_1^S(\mu) + \frac{1}{2}\delta p^*(\tilde{\mu}) s_2^S(\tilde{\mu}) > (p^*(\mu) - c) s_1^S(\mu) + p^*(1) s_1^*(1) \quad . \tag{38}$$

That is if

$$c > \frac{p^*(1) s_1^*(1) - \frac{1}{2}\delta p^*(\tilde{\mu}) s_2^S(\tilde{\mu})}{s_1^S(\mu)} \equiv \bar{c}' \ .$$

Note that $\bar{c}' > \bar{c}(0)$.

Online Appendix II: Heterogenous Effects - A Spatial Estimation Approach

In our baseline estimation of the effects on drug quality among incumbent stores, we estimate the impact of having an NGO saleswoman operating in the same village as the drug store. This seems appropriate given that the NGO saleswoman had a designated catchment area where she was allowed to operate; going door-to-door within the village. The NGO monitored the saleswomen through its branch offices to ensure compliance. Our survey data also confirms that the NGO saleswomen largely respected these boundaries, as very few households in control villages report buying medicine from these saleswomen. Therefore, the randomization was done at the village level. From an econometric perspective it is therefore quite straightforward to compare outcomes for drug stores with and without the NGO saleswoman operating in the village of the drug store; we would obviously expect the former type of stores to be much more exposed to the competition induced by the NGO.

That said, there are a few reasons to expand the analysis beyond this simple approach. First, while the NGO saleswomen were restricted geographically, the competing drug stores were obviously allowed to sell to anyone. Second, many households are located in villages without a drug store, but nevertheless have at least one store within reasonable walking distance. Villages in our sample are located relatively near to another. To see this, in our baseline household survey data, we measure how far away from a drug store each household is located. Households who have a drug store in their village are located approximately 0.6 km from a drug store, on average. For those which did not have a drug store in the village, the average distance is about 1.5 km. Given these distances, and given a walking speed of about 3-4 km per hour, it is reasonable to conclude that the majority of the households in our data have a drug store relatively nearby where they most likely buy drugs from.

Therefore, in practice the drug store's customer base is not necessarily defined by the village. Conceptually we might therefore expect some spatial spillover. Here we present a complementary analysis that takes spatial issues into account.

The analysis is based on the following features of the intervention.

1. The NGO saleswomen only competes for customers located within the village of the drug store, because of her catchment area restriction. Since she did not go door-to-door to other villages, she does not compete for those customers. When the NGO enters a given village and potentially "steals" away customers located in that village, who switch from incumbent drug stores to the NGO.

2. Any given drug store can sell to households that live anywhere.

3. In practice, the customer base of a drug store is thus defined by some radius X around the store. (We obviously do not know exactly how the customer base relates to distance, and so we empirically explore various distances.)

4. Because the drug store can have a share of its customer base consisting of households living outside the village, it can lose customers to NGO saleswomen operating in nearby villages.

5. Together, the competitive pressure of the NGO as a whole for a drug store is increasing in the share of its customer that overlaps with the catchment area of all NGO saleswomen.

The regression specification is the following:

$$y_{id} = \sum_{D=1}^{3} \beta^D * NGOCompetition_{id}^D + \theta X_{id} + \delta_c + \varepsilon_{id}$$

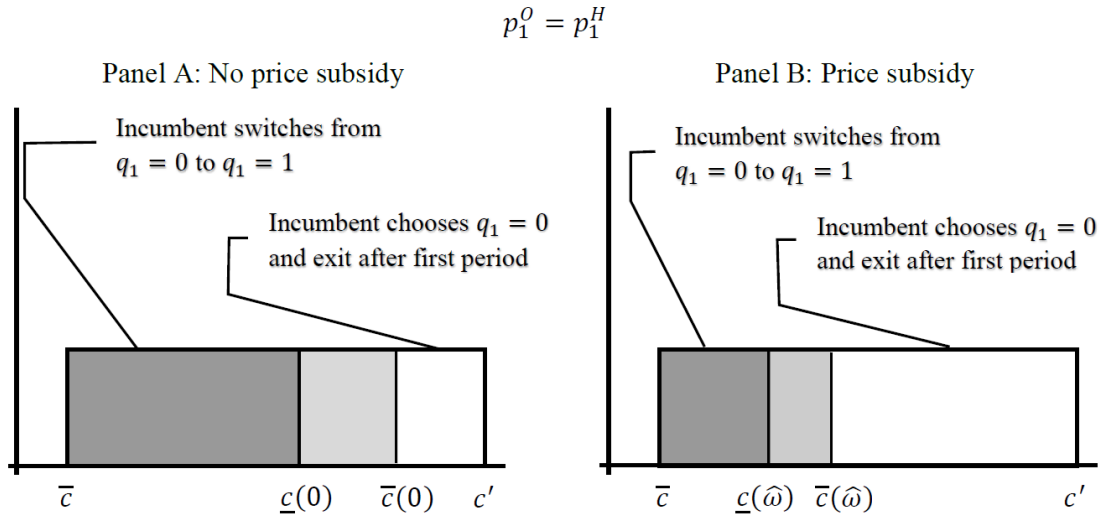
where y is some outcome (e.g., drug quality) for drug store i, located in district c. $NGOCompetition_{id}^D$ is the share of the customer base of drug store i that overlaps with catchment areas of all NGO saleswomen. We define the customer base as households living within a certain distance D from the drug store. In particular, we allow for effects up to 7.5 km, using three intervals each consisting of 2.5 km radius bandwidth: 0-2.5 km, 2.5-5 km, 5-7.5 km. We might expect effects to be monotonically decreasing in distance, since the customer base should be a function of walking distance for households (depending on walking path conditions, it would take approximately 1-1.5 hours to walk back and forth to a drug store 2.5 km away). Since households are not uniformly distributed across space, we use high resolution satellite data on the population distribution in order to measure what share of the population within a certain distance of a drug store happens to overlap with catchment areas of the NGO saleswomen.[55] In all specifications, we include district fixed effect (since randomization was stratified by districts). We also always include controls for the expected NGO competition, at each distance. That is, given that each randomization procedure specifies an equal likelihood that a given village will be selected into treatment and control group, this effectively controls for any determinants

[55]We use the High-Resolution Settlement Layer data, at a spatial resolution of 30 meters, available to download from https://www.ciesin.columbia.edu/data/hrsl/. The catchment areas of saleswomen are defined by the village boundaries. As there are no digitized maps of these boundaries, we use the convex hull of households in each village from our survey data. Thus, we may have some measurement area, but this would tend to lead to attenuation bias if the error is classical, which seems reasonable in this case.

related to the locations of the drug stores (e.g., some drug stores are located far away from high population density areas), so that the randomization realization is exogenous conditional on the control.

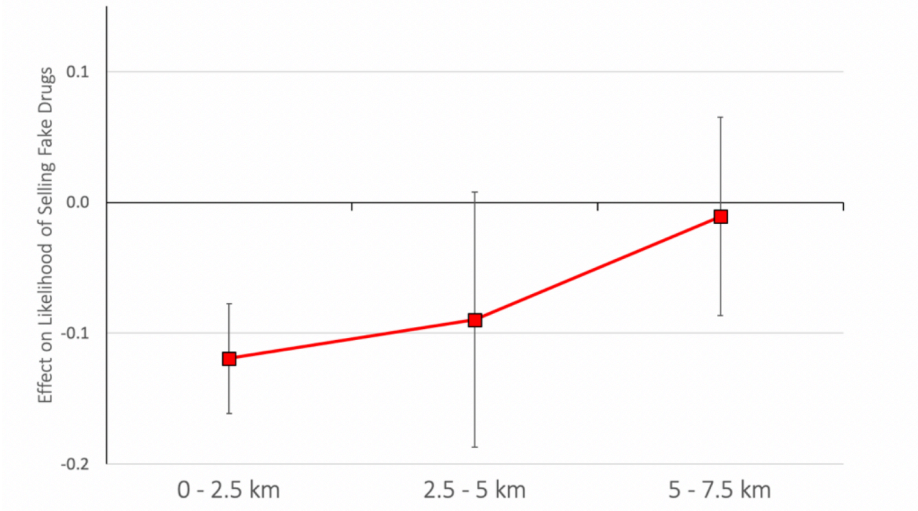
The results are available in appendix table A.1 and appendix figure A.2. Using this approach, we see that drug stores which have a greater share of their customer base nearby (within 2.5 km) overlapping with NGO saleswomen sell higher quality drugs at lower prices, on average. The effect dissipates at longer distances, as expected. These results confirm the basic story of the paper where nearby presence of NGO saleswomen induces higher quality drugs in the market.

Appendix Figure A.1: Equilibrium strategy for an incumbent with the NGO in the market



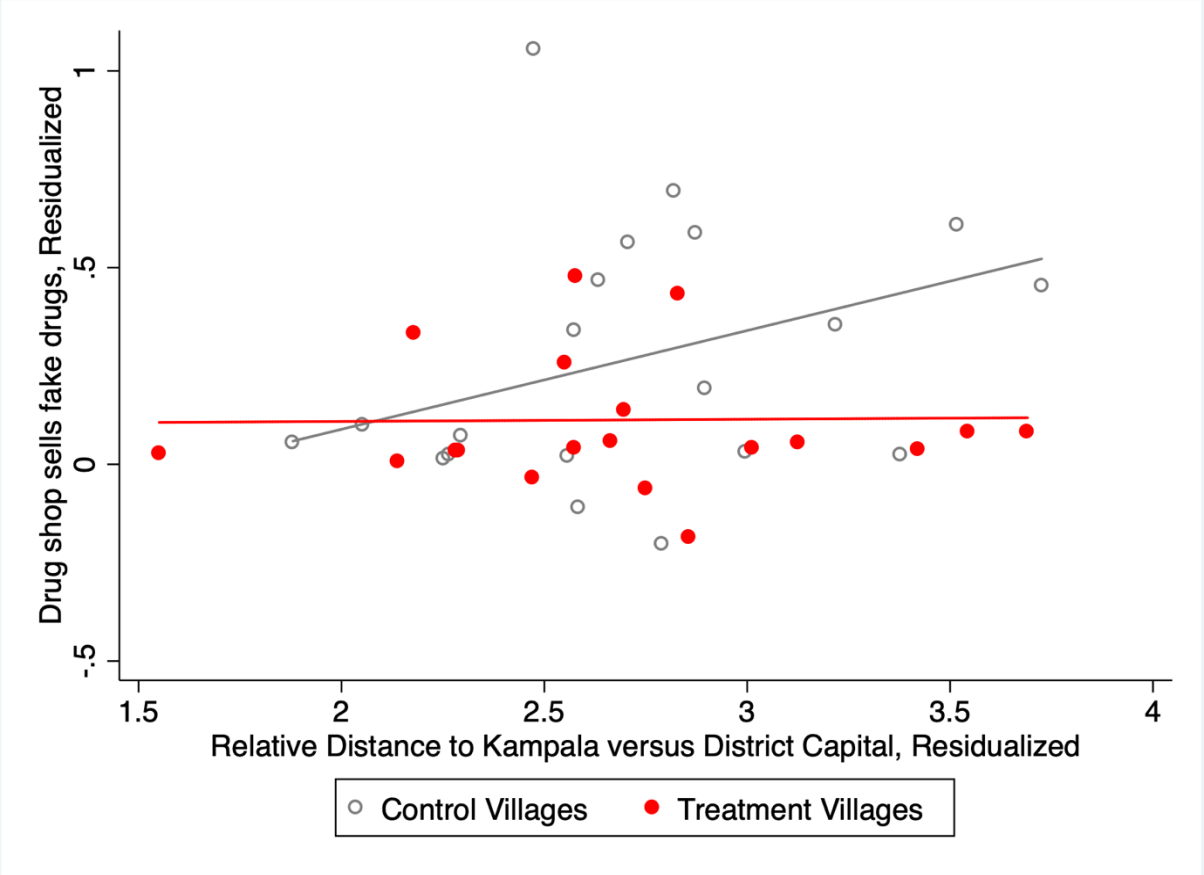
Note: The figure shows the opportunistic incumbent's equilibrium strategy as function of the incumbent's cost of supplying high quality drugs (c) when facing competition from the NGO. In panel A, the NGO sells high quality drugs without a subsidy ($\omega = 0$) and $p_1^O = p_1^H = p_1^*$, where p_1^* is the period 1 monopoly price. In panel B, the NGO sells high quality drugs with a subsidy ($0 < \omega < 1$) and $p_1^O = p_1^H = p_1^*(1 - \omega)$. High cost incumbents are more likely to exit the market when faced with competition from the NGO if the NGO sells high quality drugs with a subsidy.

Appendix Figure A.2: Treatment effect on drug quality as a function of distance



Note: The figure shows the treatment effect on drug quality as a function of distance. Specifically, using the drug store as the unit of analysis, it is the estimated effect of the share of the population overlapping with catchment areas of NGO saleswomen, at the specified distances. The results indicate that the NGO effect disappears after approximately 5km.

Appendix Figure A.3: Effects by distance to wholesalers



Note: Binscatter plots of the likelihood of drug stores selling fake drugs by treatment status of the village of the drug store. The x-axis captures the logged relative distance of traveling from the village to Kampala compared to the district capital, using Google Maps. Variables are residualized, controlling for branch fixed effect and baseline covariates. The patterns in the control group suggest that when the costs of acquiring high quality drugs versus low quality drugs from wholesalers are relatively high, prevalence of low-quality drugs is greater, and that the effect of the NGO is primarily driven by those villages with relatively high costs. One cannot, however, statistically reject that the two slopes are statistically equal.

Appendix Table A.1. Effects of NGO Entry: Quality of ACT in Drug Stores

Sample of Shops	All	All	All	Sold ACT	Sold ACT	Sold ACT
Dependent Variable:	Drug store sells fake drugs, dummy	% Fake drugs	A majority of drugs are fake, dummy	Drug store sells fake drugs, dummy	% Fake drugs	A majority of drugs are fake, dummy
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.169**	-8.87**	-0.108**	-0.217**	-11.93**	-0.149**
	(0.066)	(3.58)	(0.043)	(0.087)	(4.83)	(0.057)
Observations	135	135	135	93	93	93
R-squared	0.095	0.10	0.107	0.105	0.12	0.131
Unit of Analysis	Drug shops	Drug shops	Drug shops	Drug shops	Drug shops	Drug shops
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean in Control	0,263	13,5	0,138	0,368	18,9	0,193

Note: The unit of analysis is a drug store. In columns 1-3, the sample contains all stores identified during the baseline drug store census. In columns 4-6, the sample consists of stores that sold ACT at the time of the drug quality survey. The dependent variables are: in columns 1 and 4, a dummy indicating if the drug store sold failed drugs during the quality survey, and zero otherwise (including cases where the store was not open or did not sell ACT); in columns 2 and 5, the percent of tested drugs that failed (in column 2, this is also zero for drug stores that did not sell any drugs); in columns 3 and 6, a dummy indicating if the majority of tested drugs failed, and zero otherwise (including cases where the store did not sell ACT in column 3). Note that column 1 replicates the regression from the baseline estimates in Table 4, column 5, for ease of comparison. *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 the same as in Table 4. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Appendix Table A.2. Heterogenous Effects of NGO Entry on Quality in Drug Stores, by Baseline Competition in the Village

Sample of Shops	All	All	All	Sold ACT	Sold ACT	Sold ACT
Dependent Variable:	Drug store sells fake drugs, dummy	% Fake drugs	A majority of drugs are fake, dummy	Drug store sells fake drugs, dummy	% Fake drugs	A majority of drugs are fake, dummy
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.175**	-9.25**	-0.121**	-0.239**	-13.37**	-0.175***
	(0.076)	(4.31)	(0.047)	(0.099)	(5.52)	(0.059)
Village Monopoly at Baseline	0.061	-0.45	0.029	0.060	-3.95	0.007
	(0.159)	(8.30)	(0.109)	(0.208)	(11.01)	(0.150)
NGO entry * Village Monopoly at Baseline	0.007	1.81	0.046	0.096	7.83	0.121
	(0.184)	(9.68)	(0.129)	(0.251)	(12.32)	(0.183)
Observations	135	135	135	93	93	93
R-squared	0.097	0.10	0.110	0.111	0.13	0.137
Unit of Analysis	Drug shops	Drug shops	Drug shops	Drug shops	Drug shops	Drug shops
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean in Control	0,263	13,5	0,138	0,368	18,9	0,193

Note: The unit of analysis is a drug store. In columns 1-3, the sample contains all stores identified during the baseline drug store census. In columns 4-6, the sample consists of stores that sold ACT at the time of the drug quality survey. The dependent variables are: in columns 1 and 4, a dummy indicating if the drug store sold failed drugs during the quality survey, and zero otherwise (including cases where the store was not open or did not sell ACT); in columns 2 and 5, the percent of tested drugs that failed (which is zero for drug stores that did not sell any drugs in column 2); in columns 3 and 6, a dummy indicating if the majority of tested drugs failed, and zero otherwise (including cases where the shop did not sell ACT in column 3). *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. Village Monopoly at Baseline is a dummy equal to one if there was only one drug store in the village in the baseline drug store census. The control variables are the same as in Table 4. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Appendix Table A.3. Effects of NGO Entry: Spatial Effects

Sample of Drug Shops:	All villages, all stores				All villages, stores with ACT sold			
Dependent Variable:	Drug store sells fake drugs, dummy		Drug store exit, dummy		Drug store sells fake drugs, dummy		Log Price	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO Competition, 0 - 2.5km	-0,119	-0.124	-0.084	-0.075	-0.193	-0.191	-0.097	-0.090
S.E. Spatial Dependence: <2.5 km	(0.030)	(0.033)	(0.013)	(0.012)	(0.032)	(0.028)	(0.030)	(0.026)
S.E. Spatial Dependence: <5 km	(0.021)	(0.025)	(0.009)	(0.009)	(0.025)	(0.021)	(0.027)	(0.023)
S.E. Spatial Dependence: <7.5 km	(0.017)	(0.021)	(0.008)	(0.007)	(0.020)	(0.017)	(0.023)	(0.020)
S.E. White	(0.050)	(0.055)	(0.037)	(0.039)	(0.072)	(0.078)	(0.032)	(0.034)
NGO Competition, 2.5 - 5 km	-0.090	-0.095	0.010	-0.016	-0.121	-0.123	-0.051	-0.051
S.E. Spatial Dependence: <2.5 km	(0.070)	(0.063)	(0.053)	(0.093)	(0.062)	(0.053)	(0.033)	(0.072)
S.E. Spatial Dependence: <5 km	(0.050)	(0.051)	(0.038)	(0.067)	(0.044)	(0.040)	(0.027)	(0.053)
S.E. Spatial Dependence: <7.5 km	(0.041)	(0.043)	(0.032)	(0.056)	(0.036)	(0.034)	(0.023)	(0.043)
S.E. White	(0.100)	(0.126)	(0.073)	(0.090)	(0.127)	(0.170)	(0.056)	(0.074)
NGO Competition, 5 - 7.5 km	-0.011	-0.022	0.038	0.053	0.098	0.117	0.022	0.026
S.E. Spatial Dependence: <2.5 km	(0.049)	(0.058)	(0.037)	(0.038)	(0.054)	(0.071)	(0.045)	(0.056)
S.E. Spatial Dependence: <5 km	(0.039)	(0.050)	(0.028)	(0.029)	(0.047)	(0.064)	(0.040)	(0.051)
S.E. Spatial Dependence: <7.5 km	(0.032)	(0.042)	(0.023)	(0.024)	(0.041)	(0.054)	(0.034)	(0.044)
S.E. Huber-White	(0.077)	(0.083)	(0.056)	(0.059)	(0.103)	(0.110)	(0.045)	(0.048)
Observations	131	131	131	131	92	92	92	92
R-squared	0.292	0.300	0.292	0.300	0,139	0,159	0,573	0,591
Unit of Analysis	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop	Drug shop
Controls								
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Expected NGO Competition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village Controls	No	Yes	No	Yes	No	Yes	No	Yes
Additional Spatial Controls	No	Yes	No	Yes	No	Yes	No	Yes
Dep. Var. Mean	0,214	0,214	0,214	0,214	0,304	0,304	9,015	9,015

Note: The unit of analysis is a drug store. In columns 1-4 the sample is all drug stores with GPS data at baseline (131 out of 135 stores; data lacking for 4 stores). In columns 5-8 the sample is all drug stores that sold ACT with GPS data at baseline (92 out of 93 stores). For each drug store, NGO Competition for customers is measured within distance d, where d is: 0 - 2.5 km, 2.5-5 km or 5-7.5 km. It is defined as the log population share within the distance d from the drug store that are locate within the catchment area, i.e. the village boundaries, of the NGO. This measure is based on the fact that the CHP is allowed to sell only to the population within the village boundaries. Drug stores face no such constraint. In order to the maintain random assignment, all regressions control for Expected NGO Competition, i.e. the expected value of NGO Competition before the randomized implementation of the NGO intervention was implemented, for each distance. The village controls are the same as before. Additional Spatial Controls are the logged population within 7.5 km of the drug store and the spatial competition at baseline from other stores shops, defined as the population share within 7.5km of the drug store which also are located within 7.5 km of another drug store at baseline. OLS regressions, with Conley (1999) standard errors in parentheses which account for spatial dependence. It allows for a linearly decreasing spatial dependence up to a cutoff, 2.5/5/7.5 km respectively.

Appendix Table A.4. Heterogenous Effects of NGO Entry on Quality in Drug Stores, by Baseline Beliefs

Sample of Shops	All	All	All	Sold ACT	Sold ACT	Sold ACT
Dependent Variable:	Drug store sells fake drugs, dummy	% Fake drugs	A majority of drugs are fake, dummy	Drug store sells fake drugs, dummy	% Fake drugs	A majority of drugs are fake, dummy
	(1)	(2)	(3)	(4)	(5)	(6)
NGO entry	-0.172***	-9.16**	-0.112***	-0.214**	-12.11**	-0.149**
	(0.064)	(3.50)	(0.042)	(0.090)	(5.06)	(0.060)
% of Population Believing Drugs are Fake at Baseline, Std.	0.039	1.52	0.030	0.024	-0.45	0.012
	(0.068)	(3.80)	(0.045)	(0.089)	(4.77)	(0.062)
NGO entry * % of Population Believing Drugs are Fake at Baseline, Std.	0.013	3.68	0.043	0.063	9.38*	0.124
	(0.078)	(4.18)	(0.054)	(0.114)	(5.34)	(0.074)
Observations	135	135	135	93	93	93
R-squared	0.101	0.11	0.123	0.111	0.14	0.157
Unit of Analysis	Drug shops	Drug shops	Drug shops	Drug shops	Drug shops	Drug shops
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean in Control	0,263	13,5	0,138	0,368	18,9	0,193

Note: The unit of analysis is a drug store. In columns 1-3, the sample contains all shops identified during the baseline drug store census. In columns 4-6, the sample consists of stores that sold ACT at the time of the drug quality survey. The dependent variables are: in columns 1 and 4, a dummy indicating if the drug store sold failed drugs during the quality survey, and zero otherwise (including cases where the store was not open or did not sell ACT); in columns 2 and 5, the percent of tested drugs that failed (which is zero for drug stores that did not sell any drugs in column 2); in columns 3 and 6, a dummy indicating if the majority of tested drugs failed, and zero otherwise (including cases where the store did not sell ACT in column 3). "*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. "% of Population Believing Drugs are Fake at Baseline, Std." is the percent of the baseline survey respondents in the village of the drug store that answered they think the nearest drug store sells fake drugs; this variable is standardized to mean zero and standard deviation one in the drug store sample for ease of interpretation. The control variables are the same as in Table 4. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5% , * 10% significance.

Appendix Table A.5. Effects of NGO Entry: Beliefs about Efficacy of Malaria Medicines

Dependent Variable:	Believes ACT is highly effective, dummy		Believes non-ACT drugs are highly effective, dummy	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
NGO entry	0,011	0.007	0.013	0.040
	(0.016)	(0.015)	(0.034)	(0.032)
Observations	653	653	646	646
R-squared	0,02	0,02	0,01	0,04
Unit of Analysis	HH	HH	HH	HH
Sample of villages	Shops at baseline	Shops at baseline	Shops at baseline	Shops at baseline
Number of villages	26	26	26	26
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Dep. Var. Mean, Control	0,94	0,94	0,85	0,85

Note: Data from the endline household survey conducted in 48 randomly sampled villages (column 1 and 3), or the subset of villages that had shops at baseline (column 2 and 4). *T*he dependent variable captures whether the respondent answers "highly effective" to the question "How effective do you think that this medicine is in treating malaria today?" (options: highly effective, somewhat effective, not effective). The non-ACT medicines are Chloroquine, Quinine, and SP, and the dummies in columns 3-4 are equal to one if the respondent answers highly effective to at least one of the drugs. The control variables are the same as in tables 3-8. Robust standard errors in parentheses, clustered at the village level. *** 1% , ** 5%, * 10% significance.