Do Informed Consumers Reduce the Price and Prevalence of Counterfeit Drugs? Evidence from the Antimalarial Market

Anne Fitzpatrick*
University of Michigan

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Abstract

A defining characteristic of healthcare markets is asymmetric information between patients and providers. Healthcare providers may strategically use this information advantage to maximize their own payoff. Providers may recommend unnecessary services, increase prices, or lower quality on unsuspecting patients. I conduct an audit study using study team confederates ("covert shoppers") to test how providers would adjust price and quality if patients were relatively more informed about healthcare choices. Shoppers purchase antimalarial drugs according to randomized scripts. The scripts experimentally vary knowledge of the patient's diagnosis (malaria) and/or knowledge of appropriate treatment (artemether-lumefantrine). I then test purchased drugs to determine whether they are counterfeit or substandard. Shoppers knowing either the diagnosis or recommended treatment pay approximately \$0.18 (5 percent) less. While overall drug quality is high, relatively more informed customers are 3.4 percentage points more likely to buy a substandard drug. I interpret results through a framework where providers trade off the current benefits to strategic behavior against potential future profit losses if strategic behavior was detected. Because more informed customers pay lower prices and seek healthcare less often, there are lower potential profit losses if low drug quality were detected. I provide additional survey data from both providers and real customers to support this interpretation. Results indicate that while customer information may lower prices, providers strategically lower quality in order to maximize profits. Thus, the net effect on consumer welfare from increased information is ambiguous.

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1 Introduction

Healthcare providers have substantial power to influence the treatment choices of patients because of their superior information [Arrow, 1963]. Although healthcare providers are expected to advise treatments to maximize patient well-being, providers may instead use this information advantage to increase profits. The strategic use of information advantages is a common feature of markets with experts, such as car repairs, emissions testing, or taxi rides in a new city. Similar problems of "agency" have been found in various healthcare markets, including chemotherapy drugs, cesarean sections, and prescription medicines [Currie et al., 2011, Yip, 1998, Jacobson et al., 2010].[1] These problems arise because customers cannot evaluate what treatment or service they need without help from the expert. Customers may not even be able to identify what service was performed after purchase. As a result, providers may increase prices ("overcharge"), advise unnecessary services, or substitute lower quality to unsuspecting customers.

Asymmetric information may be a contributing factor to the problem of counterfeit, or low quality, drugs. According to a recent meta-analysis, approximately one-third of antimalarials in sub-Saharan Africa are of "low quality", a catch-all term ranging from falsified to counterfeit to unregistered but effective generics [Nayyar et al., 2012].[2] Low quality drugs may harm individuals by delaying effective treatment or wasting money. Low quality drugs are also a public health concern, as they contribute to drug-resistant diseases [Okeke et al., 1999]. However, estimating the effect of counterfeit drugs on health and well-being is difficult. The existing literature is primarily descriptive, with non-random samples and small sample sizes.[3]

This paper presents estimates of how providers would respond if customers were relatively more informed about their healthcare choices. There are few studies that have evaluated the supply-side response to decreased information asymmetries, and most studies measure responses in non-healthcare markets. Empirically, one of the biggest challenges in this literature

[1]In non-health markets, the terminology used is typically 'provider agency'. In health markets, this phenomenon is usually called "provider-induced demand" [Evans, 1974]. See McGuire [2000] or Chandra et al. [2011] for comprehensive reviews of the literature on health provider motivations.

[2]It should be noted that the imprecise terminology is a contributing factor to why counterfeit drug rates appear to be increasing over time. For example, debates over language with respect to counterfeit medicines have postponed the enactment of international agreements on low quality drug sales. It is feared that restricting counterfeit, ineffective drugs may inadvertently restrict access to effective generic formulations.

[3]Exceptions are Bjorkman et al. [2012] and Bennett and Yin [2014] who both find that competition improves quality.

is to establish a causal link between customer information and how providers respond. Customer information is not distributed randomly throughout the population, and information may be correlated with other characteristics of demand. Existing research has either focused on comparing the prices paid and services received between experts and the general population, or how providers change quality in response to public information. Levitt and Syverson [2008] show real estate agents sell their own homes for higher prices and Bronnenberg et al. [2014] show that for a variety of products, experts choose lower-priced equivalent products than regular customers.[4] The impact of public information, for example, through "report cards" reveals that increased information can cause providers to respond to maximize utility, although not necessarily in a direction beneficial to patients. While Kolstad [2013] finds surgeons improved quality due to intrinsic motivation to succeed, Dranove et al. [2003] shows that surgeons selectively refused to treat sicker patients to increase their rankings.

I conduct the first experimental evaluation to test how providers respond to types of information that an ordinary customer might present at the time of purchase: knowledge of what illness they have (diagnosis), and knowledge of a specific treatment.[5] Previous experimental work in the taxi market has found that signaling information can reduce the likelihood of being taken on a detour (over-treatment), and speaking the local language decreases the likelihood of being overcharged [Balafoutas et al., 2013]. However, improved customer information may not necessarily translate into price or quality differences. Particularly in markets for health, everyday customers or patients cannot learn the equivalent knowledge of healthcare professionals. It may simply not be possible for customers to sufficiently decrease information asymmetries, as compared to experts. Finally, information may be correlated with other inputs into healthcare demand. If providers believe information signals other characteristics of demand, such as wealth or preferences, then predicting the potential provider response to information becomes even more difficult. Whether improved customer information will result in lower prices and higher quality is ultimately an empirical question.

[4] There is a related, large body of research on whether health providers adjust treatment recommendations in response to financial incentives. For example, Johnson and Rehavi [2014] estimate how providers respond to an exogenous change in financial incentives by comparing differences in caesarean section rates when physicians give birth compared to when non-physican patients give birth. There is also a substantial literature on whether improved health information changes behavior and ultimately demand for healthcare, generally finding changes in behavior but less in terms of demand [Meredith et al., 2013, Madajewicz et al., 2007, Godlonton et al., 2014].

[5] These are the two sources of information advantages providers have over patients, and are the types of information that patients might potentially present at the time of service [Wennberg, 1985].

In order to evaluate the effect of improved customer, I implement a randomized audit study. Covert shoppers purchase drugs according to randomly assigned scripts that vary in information regarding the patient's diagnosis and/or knowledge of appropriate treatment. Shoppers then fill a survey on the transaction, and all purchased drugs are tested for quality. I then compare mean differences in outcomes between covert shoppers reciting the randomly assigned scripts. I find that health providers do exhibit agency, and adjust prices and quality in response to the randomized customer information. Improved customer information lowers prices by \$0.13 - \$0.18 (5 percent) and drug quality decreases by approximately 3.4 percentage points. In contrast to previous studies, I find that drug quality is relatively high. I find that while 17 percent of antimalarial drugs can be classified as counterfeit, 80 percent of counterfeits are chemically effective. I estimate that approximately 4 percent of all purchases are of substandard quality. Although I caution that substandard drugs are relatively rare, I find that nearly all of the substandard drug purchases are among customers with information. Service quality also falls substantially, by approximately 8 percentile points.

I provide additional evidence from both vendors and real customers to understand the mechanisms of how information affects prices and quality. I test whether decreases in quality simply reflect decreases in price. I estimate hedonic regressions which indicate that service quality is significantly correlated with price, although drug quality is not. These estimates may also explain why individuals do not learn simple, yet beneficial information: information may not be as valuable if it lowers prices, but also lowers service quality.

In contrast, the negative relationship between information and drug quality may be driven by a different mechanism. I consider a framework where firms trade off current benefits from strategic behavior against the potential future profit losses if strategic behavior was detected [Schneider, 2007, Dulleck and Kershbamer, 2006]. The penalty from detection is the loss of that customer's future business. In this context, information regarding diagnosis or treatment does not signal an improved ability to detect substandard medicines. Therefore, the higher profits from low information customers leads to higher drug quality, because there are larger profit losses if that customer detected low drug quality.

This study improves internal validity issues plaguing the existing literature on provider motivation in health markets through a randomized design in an appropriate setting. I isolate the effect of improved customer information through experimentally varying scripts used at the time of purchase. This design rules out customer behavior and preferences as confounding characteristics while measuring provider responses during the transaction. In addition, the treatment recommendations for malaria are straightforward and relatively constant across all patients. Thus, provider responses have a clear interpretation, as opposed to a "gray" area of medicine where different healthcare costs may simply reflect patient-specific differences in appropriate treatment choices. Finally, the Ugandan market is primarily characterized by fee-for-service providers, without health insurance or other third-party payment systems.

This paper measures the impact of improved customer information on prices and quality in an important market for global health. Malaria is widespread disease throughout sub-Saharan Africa with severe economic and health consequences.[6] Despite its prevalence, there is substantial evidence of low average customer information and widespread misconceptions with respect to both malaria diagnosis and treatment. The findings presented information campaigns and empowering customers regarding their purchases would likely be a relatively low-cost intervention to reduce prices, and complementary to widespread subsidies. However, I conclude that it is the lower prices may simultaneously increase low drug quality rates by decreasing the pecuniary penalties of strategic behavior. On the other hand, low quality drugs are relatively uncommon. Because both drug quality and drug prices are relatively high, results suggest that more resources need to be allocated towards lowering drug prices for those who need it, as opposed to improving drug quality. In addition, the findings in this paper support the view that there are few barriers to accessing malaria treatment when perhaps there should be more. Only 3 percent of shoppers purchasing for a fictitious patient report being denied a sale without testing the patient for malaria; according to official regulations, all sales should have been denied to prevent drug-resistance from unnecessary utilization. These data indicate that improved customer information does not improve the allocative efficiency of antimalarial treatment.

This paper is organized as follows. In Section 2, I outline why the private sector for antimalarial drugs makes for an ideal setting for testing improved customer information. I describe the study design in Section 3, and in Section 4 I summarize the collected data. I present the conceptual framework in Section 5, and in Section 6, I present the empirical

[6] It is estimated that expanded access to first-line antimalarial treatment will reduce mortality and morbidity, and also can improve productivity and incomes by as much as 12 percent [Dillon et al., 2014].

strategy. In Section 7, I summarize my results and in Section 8 I discuss mechanisms and policy implications. In Section 9, I conclude and discuss areas for future research. Appendices are available on my website.[7]

2 Study Background

Healthcare markets in Uganda differ substantially from regulated markets in developed countries. I first outline the problem of low quality medicines. I describe how this study contributes to the nascent literature on this potential threat to individual well-being by testing a hypothesized cause: low customer information. Next, I give background specific to the anti-malarial treatment. I then characterize the demand and information problems in this market. I conclude with a discussion of antimalarial drug supply in Uganda.

2.1 Drug Quality

The literature on counterfeit and low-quality drugs in developing countries is primarily descriptive. Existing work documents that low quality medicines, and specifically anti-malarial drugs, are found across a range of countries. According to a meta-analysis, nearly one-third of antimalarials in sub-Saharan Africa are low quality [Nayyar et al., 2012].[8] However, many of the included studies use non-random sampling methods and have small sample sizes. Building a sample frame in a largely informal market is difficult, and determining whether a drug is low quality typically requires time-consuming chemical assays and dissolution analysis. For example, only six of the twenty-eight studies cited rely on random sampling methods, and only three of those studies based upon random sampling have more than 50 observations.[9]

As a result of these data and design limitations, the average rate of low quality drugs is uncertain. Although it is believed that low quality medicines increase individual morbidity and mortality, the precise impact on human health and welfare is unknown. In addition, it is unknown which interventions are the most cost-effective for reducing this problem. Recent

[7] http://www-personal.umich.edu/~fitza/research.html

[8] For a summary of the existing literature, see Kelesidis et al. [2007].

[9] There are other methodological problems in the existing literature. In particular, the definitions and classification criteria of low quality, fake, or substandard are not consistent across the studies in the cited meta-analysis. This is likely due to different official pharmacopeia guidelines by country and the variety of drug testing methodologies used. I use the guidelines for low-quality medicine studies, and apply the definitions of Newton et al. [2009] throughout this paper.

studies have used larger sample sizes and randomized designs to find that high quality competition both drives down prices and improves drug quality [Bjorkman et al., 2012, Bennett and Yin, 2014]. It has yet to be evaluated whether demand-side interventions, such as customer information, would be effective at improving drug quality.

2.2 Malaria and Treatment

Low quality anti-malarial drugs in particular may be problematic for public health because of the large burden of malaria in developing countries. Although malaria is a treatable disease, it is the second leading cause of death for children under the age of 5 and the most common illness in Uganda. The average child has approximately 2 episodes per year, and the average adult has approximately an episode every other year.[10]

For patients of all ages, the recommended first-line treatment for malaria in Uganda is artemether-lumefantrine (AL). The clinical efficacy of AL for uncomplicated malaria ranges from 95-100 percent for both adults and children [Makanga and Krudsood, 2009]. AL is preferred over older therapies, such as sulphadoxine-pyrimethamine (SP) or chloroquine, which are no longer clinically effective due to drug resistance [Baird, 2005]. AL is part of a larger class of medicines known as artemisinin-based combination therapies (ACTs) that combine different effective therapies together to limit future drug resistance. Quinine, another commonly available treatment, is intended to be reserved for more serious cases of malaria ("complicated"), or as a second-line treatment. Despite the availability of effective treatment, approximately one-third of symptomatic children do not receive first-line treatment, likely due to a combination of high prices and low levels of caregiver health knowledge (DHS, 2011).

2.3 Demand and Asymmetric Information

Although malaria is a common disease, there are low average levels of customer information. There are two related factors contributing to why customer information regarding malaria treatment remains low: a reliance on symptomatic diagnosis, and low levels of health knowledge.

According to official WHO guidelines, antimalarial drugs should only be given to adults

[10] In Uganda, malaria is endemic throughout 90 percent of the country all year round. However, there are additional peaks following rainy seasons.

following a positive malaria test, either through blood microscopy or rapid diagnostic testing. The symptoms of malaria overlap with the symptoms of other bacterial of viral infections, thus making symptomatic diagnosis highly error-prone. However, testing is often unavailable, approximately the same as the cost of treatment, and there is low adherence to testing results. As a result, that only 39-53 percent of adults seeking treatment for malaria at private sector facilities test positive according to a blood test [Littrell et al., 2011, Cohen et al., 2012]. Adhvaryu [2012] shows that repeated misdiagnosis introduces noise and impedes the adoption of new medical treatments. The over utilization of unnecessary care, is concerning from a public health perspective because it increases drug resistance.

There are also problems of low health literacy. Numerous studies have demonstrated low levels of customer information about malaria transmission, diagnosis, and treatment in a variety of countries and settings [Nuwaha, 2002, Deressa et al., 2003, Comoro et al., 2003]. For example, although individuals typically know that malaria is transmitted via mosquito bites, individuals also mistakenly believe malaria is transmitted through drinking bad water or unripe mangoes. These misconceptions have been linked with fewer preventive practices, choosing less effective treatments, and buying low quality medicines [Comoro et al., 2003, Deressa et al., 2008, Bjorkman et al., 2012].[11] Although knowledge of malaria transmission may not be observable to providers at the time of purchase, there are no studies to my knowledge demonstrating that knowledge of diagnosis or appropriate treatment affect utilization and transaction outcomes.[12]

2.4 Supply of Antimalarial Treatment

Anti-malarial treatment is available at both public and private providers. In 2001, Uganda eliminated user fees and made antimalarial treatment available for free in the public sector. However, quality is low in the public sector. There are long waiting times, drug stock-outs, and reports of rude staff [Konde-Lule et al., 2012, Xu et al., 2006].[13] Contributing to the drug stock-outs is that drugs are diverted from the public sector to the private sector. In order to

[11] These are the measures that the Measure DHS survey Malaria Indicator Survey currently uses to evaluate health literacy and treatment-seeking.

[12] Drug advertising in Uganda is prohibited. Although there are advertising campaigns for subsidized first-line treatment, customers primarily seek information through providers.

[13] In addition, public facilities are not conveniently available for much of the population. 41 percent of Ugandans report that distance to a public health facility deters them from seeking treatment [Uganda Bureau of Statistics, 2012].

deter resale, public-sector drugs have specific markings on the tablet and the pack. Although there may be extenuating circumstances, it is likely that drugs with public sector markings are taken from public facilities, where they are free, and sold illicitly in private facilities. In my data, 8 percent of purchases from private sector outlets appear to be diverted.

In response to problems in the public health sector, between 60-80 percent of those seeking care for malaria choose to first seek care in the private sector [Konde-Lule et al., 2012, Littrell et al., 2011, Uganda Bureau of Statistics and Macro, 2010]. It is estimated that there are approximately 17,000 drug shops and clinics throughout the country, and 440 registered pharmacies [Uganda Bureau of Statistics, 2012]. Although there are officially clear distinctions between drug shops and clinics, including regulatory and minimum education requirements of owners, in practice the difference may be indistinguishable to customers.[14] In contrast to qualified public sector providers, providers in the private sector may be unlicensed and lack minimum qualifications. Up to 60 percent of drug vendors operate without the regulated medical qualifications and licensing [Stanback et al., 2011].[15]

Policy has therefore focused on increasing access to treatment through private sector outlets. Approximately $500 million has been spent through the Global Fund's Affordable Medicines Facility-Malaria (AMFm) to increase access to ACTs throughout sub-Saharan Africa through large-scale manufacturing subsidies in the private sector.[16] However, first line treatment is still unaffordable for many people. For example, the price of AL in my data is $3.19, three times higher than the target price of approximately $1. There is currently no regulation on prices in Uganda.

3 Study Design

The audit study randomly varies what information a customer presents at the time of purchase. Fieldwork took place from May-August 2013 and consisted of several rounds of data collection.

[14]Clinics are more likely to charge consultation fees and have beds in my data. However, reported establishment type may be different than the store signage.

[15]This figure is roughly in line with what I calculate using available data, that only 21-38 percent of dispensers have the minimum level of required qualifications.

[16]This figure is estimated, and likely a substantial underestimate of the costs of initiatives to improve first-line antimalarial usage. The annual budget for the AMF-m is $8 billion, of which approximately 20 percent is for medicines in both the public and private sectors. There are other large-scale foreign aid programs that also contribute funding for treatment, such as the President's Malaria Initiative, as well as numerous active NGOs.

First, the sample frame was constructed by doing census of randomly selected areas. Second, two different mystery shoppers visited each outlet and each purchased a drug. Third, additional survey data were collected from the drug dispenser at each outlet, and also real customers as they were exiting the outlet. Figure 1 contains the project timeline. In this section, I describe the experimental methodology and study protocol.

3.1 Sample Selection

Uganda is composed of 112 districts that are divided into counties; each county is further divided into subcounties; each subcounty is divided into parishes; each parish is then divided into villages.[17,18] Within selected study districts, I randomly selected two rural and two urban subcounties in each district.[19] Within each subcounty, I randomly selected two parishes within the urban subcounties and three parishes from rural subcounties, totaling 10 total parishes in each of the five districts. However, due to administrative reasons (such as fewer parishes in the subcounty) the total number of parishes in the study is 45, containing 142 villages with at least 1 drug outlet.

Study team members then conducted a census and mapped all drug outlets within study parishes with a corresponding physical description of the outside of the premises. I define drug outlet as "an immobile establishment that sells anti-malarial drugs for profit", and in practice consists mostly of drug shops, pharmacies, and medical clinics.[20] Vendors in all outlets found during the census were considered target respondents. The final sample size of shops used in the primary analysis is 459. Appendix C describes the power calculations informing the design, and Appendix D describes how the analysis sample was created.

[17]According to the 2002 census, the average size of a parish is 4,625 people; the average size of a sub-county is 25,289. Average sizes of villages were not reported [Uganda Bureau of Statistics, 2008].

[18]The number of districts at the time of data collection was 112. In order to increase access to rural areas, the government is continually subdividing districts and by 2015 there will be 136.

[19]Bushenyi, Busia, Mbarara, Rukungiri, and Kampala (the capital) were chosen as study districts due to their proximity to borders and their relative size in different regions of the country.

[20]Note that this definition does not require that the establishment actually make a profit. There are also a small number of other types of outlets that I include in the study. For example, individuals who sell antimalarial drugs out of their homes, or shops which specialize in another market, such as hardware stores, which also sell anti-malarial drugs. However, herbal shops are excluded from the sample frame, as well as charitable or public sector hospitals or pharmacies.

3.2 Experimental Design

The experimental design is pictured in Table 1 and consists of one "control" script and three "treatment" scripts, resulting in four randomly assigned scripts. I implemented randomization such that each script had an equal probability of selection and no outlet was assigned to receive the same script twice. Randomization was stratified by parish.

Two different mystery shoppers visited each drug outlet and each recited a different randomly assigned script. The experimental protocol was implemented to simulate a typical shopping experience and hold constant all behavior except for the randomly assigned script. In all scripts, shoppers first entered the shop and greeted the shopkeeper.[21] The shopper then described the four clinical symptoms of malaria (headache, fever, shivering, and body aches) for the patient, either an uncle or a father, who was back at home.[22] Then, shoppers either 1) said that they think that the patient has malaria, or 2) asked for a diagnosis,to which there was nearly always a response of "malaria".[23] Shoppers then either 3) asked for artemether-lumefantrine (AL), the WHO-recommended first-line treatment of malaria, or 4) asked for a product recommendation.[24] A picture of the protocol is in Figure 2. Additional details related to training and shopper behavior are outlined in Appendix F.

3.2.1 Drug Purchases

The study protocol gave all shoppers a standardized budget and directions on bargaining. Although I was not able to fully control all aspects of the bargaining process, I justify the study approach and discuss how I empirically handle concerns of endogenous bargaining.

All shoppers were given \$3.86 (10,000 UGX) in small denominations of used-looking money

[21]Scripts were carried out in local language, aside from Kampala and Busia where English was used occasionally.

[22]The patient was also randomly assigned independently of the shopper scripts.The patient was chosen to be an adult male in the household in order to remove the possibility of pregnancy, for which there are different guidelines for treatment. The patient was not the shopper themselves to limit suspicion based upon bad acting or the possibility of denied sale from failing a malaria test or lacking other clinical symptoms. The motivation for having two different patients was to limit the suspicion of the shopkeeper; there was not predicted to be a significant difference in price across patients. I control for this randomization in all specifications, and the coefficient on the dummy is insignificant in nearly all specifications.

[23]If the vendor responded something other than malaria, then the patient was told to consider the response and then ask whether or not it could be malaria. In practice, a vendor only responded with another illness in two transactions.

[24]In the vernacular, AL is called "coartem". To prevent any confusion with the originator brand Coartem®, by Novartis, I use the "AL" throughout.

to pay for all transactions.[25] All mystery shoppers asked how much the offered product cost, and then (after learning the price) bargained and bought a full adult dosage. The definition of "full adult" dosage was defined by the shopkeeper.

A potential concern is that vendor recommendations would endogenously change shopper preferences. Therefore, in scripts where shoppers asked for a recommendation it would no longer be clear whether the resulting purchase and prices reflected shopper or provider behavior. I overcome this challenge by implementing a drug purchase protocol in the event that multiple products were presented to them in the course of the transaction. The following is the protocol for purchasing drugs:

1. Buy the cheapest brand of AL offered.
2. If a full dose of AL was not available, buy quinine.
3. If a full dose of quinine was not available, then buy the next cheapest antimalarial available (typically SP).
4. Buy any other antimalarial.
5. If a full dose of any antimalarial was not available, they should not buy anything.

Shoppers then purchased the drug and filled a survey on the transaction. Shoppers then filled a survey on details of the transaction. The total number of antimalarial options and details on up to three were recorded. In addition, shoppers recorded measures of service quality and other products offered. Shoppers were monitored by their supervisors to ensure that they did not share information regarding price or availability between visits or across shops. The supervisors also did other quality control checks to ensure that the shoppers visited the correct shop. For example, supervisors followed or led shoppers to shops in dense areas or where shops would be difficult to find in a manner that would not attract extra attention.

3.2.2 Bargaining Protocol

In this market, only 2.2 percent of prices are posted. Therefore, mystery shoppers were also given directions on bargaining. They were told specific answers to common questions and told

[25] The per-transaction amount was based upon the pilot. This drug payment allocation does not include transportation or other costs, which were administered separately. If the final price the shopper was asked to pay was more than \$3.86, the shopper returned to their supervisor for additional money, and then went back to the store to complete the transaction. In 7.6 percent of transactions the price paid was more than this amount.

to limit bargaining to three rounds. However, there was slippage in the implementation of this aspect of protocol. Anecdotal evidence from supervisors suggests that shoppers resisted these guidelines. Shoppers were concerned that by limited bargaining they would not get a good price.

I address the potential effects of endogenous bargaining in several ways. First, all shoppers were assigned to recite all scripts. Shoppers, and their characteristics, are then uncorrelated with scripts. Second, I include shopper fixed effects in all specifications. However, there may be a remaining concern that shoppers present differential bargaining power when reciting certain scripts. Therefore, I also present both the offer price and the final transaction price as outcome variables, and also in the calculation of per-transaction profits. Offer price was determined pre-bargaining, and thus was not affected by a potentially endogenous process. In practice, the results are invariant to which measure is used.

Mystery shoppers were not allowed to retain the balance of their purchases.[26] In this context keeping the balance is not incentive-compatible. First, it is possible to buy less than a full dosage. Theoretically, shoppers could buy a half dose, state they were sold a full dosage, and pocket the difference in price between half and full dosage. There was no incentive in the current design to buy less than a full dosage, and this occurred in 8 percent of transactions. Second, a related issue is that shoppers could opt to buy a cheaper drug, such as SP, and keep the balance, while reporting that AL was out of stock. Third, if shoppers believed that the supervisors were going to alter the budget given to them at some point going forward, such as in less expensive areas, then that also might have induced them to alter their prices. Fourth, in real life when a purchase is made with excess cash, an individual is not allowed to keep the balance. In particular, returning the balance would be expected when the balance may be a large amount of money. In this context, the excess balance would have been the equivalent of a windfall of cash, particularly over the entire course of employment. Training individuals to overcome their norms was not deemed compatible to the goals of the project.

It is not expected that this aspect of protocol introduces bias into either the level of prices, or the difference in prices between scripts. Shoppers knew that there were multiple visits to the same outlets. Thus, they believed that any price differences between shoppers would have

[26] Retaining the balance and honestly reporting the price is a common feature of studies of bargaining to ensure shoppers act as they would in real life.

been regarded with suspicion. If shoppers did manipulate the reported price, that would need to be done in a manner correlated with the randomly assigned script to introduce bias. I find this unlikely, because neither shoppers nor supervisors were told the study expected to find price or quality differences between different scripts.

3.3 Mystery Shopper Data Summary

In total, 1126 attempts to purchase medicine were made, and 90 percent resulted in a successful visit, defined as an interaction with a provider in which a script was recited (N=1016). Visits to the same outlet typically occurred the same day, several hours apart.

Overall 89 percent of shops in the sample received 2 visits. The remaining received a different number of visits: 2.27 percent received 1 visit; 6.19 percent received 3 visits; and 0.62 percent of shops received 4 visits. The number of shops visited differs from the target of two per shop, because 1) visits where the script was done incorrectly were repeated at a later time; 2) some shops were found during later stages of data collection to be the same as a neighboring outlet. In those instances, I combine them into one outlet for purposes of analysis, meaning that they are treated as one cluster. I include visit order as a covariate in all specifications. In practice, results are invariant to whether or not this variable is included, although it does absorb a fair amount of residual variation. Random assignment is uncorrelated with the number of visits per shop (not shown).

4 Data & Descriptive Analysis

I first summarize the primary outcome measures used in the empirical analysis: prices and drug quality. Next, I summarize additional data collected from vendors and real customers, and describe how I use that data to calculate profit margins. Finally, I demonstrate information asymmetries and show that providers have market power.

4.1 Drug Prices: Mean and Variance

During mystery shopping, 933 drugs were successfully purchased in 1016 visits to outlets. Figure 4 graphically demonstrates that there is substantial price dispersion among anti-malarial drugs within a village. Table 3 shows average drug prices by type of active ingredient among purchased drugs. Overall, AL (the first-line treatment) is the second most expensive drug at \$3.19, following other first-line treatments. Even though some brands of AL are heavily subsidized, it is still expensive for the population. It is is also the most commonly purchased drug in the sample, indicating a large amount of availability throughout the selected study sites in Uganda, in contrast to previous work on widespread stockouts in this sector.[27] AL is more expensive than SP (an older therapy), likely because SP is no longer considered effective.

Mean price differences mask the substantial variation in prices, even for the same type of drug. Panel B of Table 3 shows the average differences in prices by brand for AL, for each of the 7 brands purchased during mystery shopping. Most of the variance in price is across-brand differences. Within the sample of AL used in the analysis, only 6 percent of variation was within-brand variation. The price of AL ranges from an average of \$2.85 to \$3.86. The distribution of prices is graphed in Figure 3. Observed prices paid for a full dosage in the sample range from \$0.19- \$25.07, and the coefficient of variation (CV) is 0.501.[28] The variation in Uganda is substantially higher than in the US context. Sorensen [2000] finds in the US market that, for a given prescription drug, the highest price is 50 percent over the lowest price, and the coefficient of variation is 0.22. He attributes the observed price variation to differential benefits from consumer search. Bronnenberg et al. [2013] also find that there are also substantial price differences between generic and originator brands in the US market for over-the-counter medicines. The authors attribute observed price differences to lack of customer information regarding drug equivalencies.

4.2 Drug Inspection and Quality Testing

At the conclusion of the fieldwork, all purchased drugs were inspected by research assistants and later tested for quality. The recorded drug characteristics include brand, expiration date,

[27]Ninety-two percent of vendors responding to the survey reported selling AL, even if they did not have it in stock at the time of the survey. Only 36 percent of outlets report that AL is their most expensive drug. This is in stark contrast to the findings of O'Connell et al. [2011], conducted in 2009, who find that only 13 percent of had any antimalarial in stock at all. Conditional on having any antimalarial in stock, the authors find that first-line treatment was available at 20 percent of private sector outlets in Uganda. The large difference is most likely due to increased policy focuses on providing access to ACTs, as through the AMF-m program. In addition, there may be methodological differences. Those researchers did not use a mystery shopper experimental methodology. Inventory may be a sensitive question, particularly for unregistered outlets, and vendors may therefore have an incentive to report a lack of stock.

[28]Phelps (1992) has an intuitive explanation of CV. He notes that as a rule of thumb, the CV is approximately ten times the ratio of the highest to lowest value. "If the CV for appendectomy is 0.30, then the ratio of high/low will be roughly 3." (p.24).

number of tablets, and whether the drug had public sector markings. New data from the drug testing analysis allow me to make a distinction between counterfeit and substandard. This is an important measure to consider in light of existing research that as many as one-third of antimalarial drugs in poor countries are counterfeit.

All purchased drugs were shipped to a laboratory at the University of Michigan for testing with a handheld Raman spectrometer, the TruScan™ RM.[29] Testing consists of comparing a purchased tablet with a separate, high-quality authentic tablet of the same brand.[30] The collection of high quality tablets forms the "spectral library". As part of testing I collected high-quality tablets from manufacturers and wholesalers in Uganda, and built a spectral library for the study. Each purchased tablet was tested at least once. The testing protocol, with additional information on storage and handling, is detailed in Appendix E.

4.2.1 Analysis Sample

A high quality tablet was obtained for 94 percent of samples (N=879). The reason a high quality tablet could not be found is typically because the samples had no identifying brand information, or the brand was not registered for sale within Uganda. In order to maintain a consistent sample throughout the analysis, I restrict the sample to be the 879 drug purchases that could be reliably tested. I document when results differ between the full sample and the analysis sample.

4.2.2 Counterfeit vs. Substandard

In order to do analysis at the transaction level, I define "counterfeit" as a purchased dosage ("sample") that has at least one tablet failing the spectrometry analysis. Because many brands are chemically similar, in practice a tablet that failed the comparison against its own high quality brand could potentially match against another brand within the library. I define "substandard" as a purchased sample that has at least one failing tablet that could not be found to match any high quality tablet spectra in the library. An example scan distinguishing

[29] This machine was loaned to me by Thermo-Fisher Scientific.

[30] Strictly speaking, a handheld spectrometer compares Raman spectra, or signatures, of two molecules. The spectrometer detects changes in the wavelength of light that occurs as part of an energy shift ("Raman shift") when the molecule is struck by a laser. This wavelength is consistent and unique to a particular molecule, the combination of active ingredients and binding agents, tablet coatings, etc., making testing brand-specific.

between counterfeit and substandard is presented in Figure 5.[31] The ability to cross-check the authenticity against other brands is an advantage of creating a large spectral library, and testing a large number of brands of the same active ingredient.[32]

4.2.3 Drug Testing Results and Comparison to Previous Studies

In total, 19.1 percent of tablets failed the handheld spectrometry test, and 17 percent of purchased drug dosages had at least one failing tablet. Additional analysis found that only 3.4 percent of samples had at least one tablet that could not be matched to any authentic brand within the library and are substandard. Results from a chemical assay that will conclusively determine medical efficacy are not yet finished.

These results are lower than the average estimates of Nayyar et al. [2012]. However, they are comparable to the results of the 2008 study in Uganda by Bjorkman et al. [2012] which found 21 percent of drugs were counterfeit. My analysis implies that while counterfeit drugs are relatively common, substandard drugs are substantially less common than previously thought.

It is important to note that I cannot conclude that Bjorkman et al. [2012] would have also found a low prevalence of substandard drugs for two main reasons. First, in between the two studies there was a major event in the antimalarial drug market, and, second, the samples are not comparable. In 2012, the Ugandan drug regulator, the National Drug Authority, closed a large, national manufacturer of substandard anti-malarial drugs. This event was highly publicized throughout the country [Mugisa, 2012]. Closing down a low-quality manufacturer would have a direct effect of eliminating a primary source of low quality medicines, and an indirect effect of causing competing firms to increase quality to avoid closure. Secondly, the sampling methods between our studies differ substantially and have little overlap. Bjorkman et al. [2012] use drug outlets located in project villages in exclusively rural areas, and 55 percent are monopolists. My results are based upon random sampling methods from both urban and rural areas, and only 6 percent of vendors are monopolists. However, my methodology should

[31]For example, assume brand A has a high degree of internal variability. A potential outcome could be that a mystery shopper purchase of brand A does not match against the high quality tablet of brand A, although it does appear consistent with the high quality tablet of brand B.

[32]Recent work by Bate et al. [2012] also differentiates between counterfeit and substandard medicines, although the authors use chemical assays and different definitions. Those authors find that 10 percent of a popular antibiotic fail testing, and 41 percent of failures contain too little of the active ingredients. My definitions are not directly comparable to the definitions of counterfeit or substandard in Bate et al. [2012], but rather reflect the current definition of counterfeit and substandard according to the WHO and Newton et al. [2009].

reflect the average drug quality rate at the time of data collection.

4.3 Surveys of Real Customers

Surveys were conducted with 867 real customers from 350 shops; 372 customers purchased an antimalarial drug. Although enumerators were targeted to interview 3 customers purchasing anti-malarial drugs from every shop in the study, in practice this was not achieved due to a high refusal rate (37 percent).[33] In addition, in some sample areas it was common for children to be sent to the outlet to buy medicine. Our protocol required that customers under 18 were not interviewed.[34] As a result, there is an imbalance in the number of interviews per outlet. In Appendix Tables A5 and A6, I show that the characteristic most associated with both whether any customer was interviewed and the total number of customers interviewed is the total number of customers. In particular, there is no correlation between prices and quality and whether or not real customers were interviewed a the store.

Results from surveys of real customers suggest that the experimental protocol was not unusual for vendors to observe. On the survey, approximately half of customers buying anti-malarial drugs (52.3 percent) reported asking for both a diagnosis and a product recommendation, and 23 percent reported asking for neither a diagnosis or a recommendation. Between 12-13 percent asked for either a diagnosis or a recommendation, but not both. Similarly, 48 percent of antimlarial customers report successfully bargaining over the price of the drug, and 53 percent of antimalarial customers were buying for another adult within the household.

4.4 Provider Characteristics

The vendor survey covered topics ranging from dispenser background and knowledge regarding malaria to profits and the operating environment. The survey was completed by 452 vendors, an 89 percent completion rate in the analysis sample. There is no correlation with price or quality in survey completion. Correlates of survey completion are in Appendix Table A1.

Table 2 contains selected summary statistics of vendor characteristics. Respondents to the

[33]There was no incentive for the exit interviews given to respondents. During pilot testing a bottle of water was provided to exit interview respondents. This attracted excessive attention in the study areas, such as individuals (who were not customers) approaching enumerators asking to be interviewed. Therefore we did not provide incentives for this aspect of data collection in the full study, potentially decreasing consent rates.

[34]A precise figure of how common children shoppers are is unavailable. No data was collected of respondents who were not over 18.

survey on average are 30 years old and only 23 percent are male. Only 8.9 percent of respondents were living in the same parish that they were born in; this is anecdotally due to the fact that it is difficult to make profits when selling to friends and family members. I estimate that 36 percent of respondents meet the legal qualifications for dispensing drugs.[35] Despite the lack of legal qualifications, available evidence suggests that vendors have relatively more information than their customers. The average vendor had been in that line of work for 6.2 years. Providers score higher than customers on a standard test of malaria transmission understanding, 81 percent compared to 72 percent. 84 percent of respondents correctly identified the first-line treatment for malaria (AL).[36]

Panel B contains characteristics of the outlets and customers in the study relevant to the analysis. Vendors report that their stores receive on average 22 customers per day, of which approximately 6 are seeking malaria treatment. Respondents report that they know approximately 43 percent of their customers by name. Thus, new customers are not necessarily unusual for vendors, even in relatively rural areas. Consistent with responses from real customers, 65 percent of vendors report that customers ask them for advice on what to purchase, and 66 percent ask for a diagnosis. 53 percent of vendors report that customers could test for malaria at their outlet; conditional on selling a test, the price was $1.09. Nearly half indicated that their outlet had beds to consult or treat patients, although only 14 percent report ever charging a consultation fee for treatment.

Outlets are small, somewhat profitable, and generally have market power. There are on average have 2.4 employees, and regulation was reported to be relatively high in the study area. 72 percent of outlets indicated that they had been inspected by a regulator from the National Drug Authority, the relevant governing body in the previous 6 months. Outlet profits are highly skewed. Although the average monthly profits are (in USD) $436, the median value of monthly profits is $77.13, with nearly 9 percent of outlets reporting negative profits for the previous month.[37] The collected data also suggests that vendors have market power. On average there are 10 outlets (including the respondent's outlet) in their market . The median

[35] These requirements vary based upon the establishment type, and (for clinics) how long the individual had their degree [Council, 2014].

[36] Information is far from complete. Only 28 percent correctly stated the full drug protocol.

[37] Profits in informal micro enterprises are notoriously difficult to measure [de Mel et al., 2009]. On the survey we allowed for corrections to reported sales and costs. In addition, if a vendor reported negative profits, enumerators asked why the value was negative to check for mistakes. Vendors generally gave responses consistent with negative profits, such as "low sales"', or "regulators seized drugs".

value is 5 competing outlets. I construct the Herfindahl Hirschman Index, a common measure of market power based upon shares of sales in the market. The index, which ranges from 0 (perfect competition) to 1 (monopoly) is 0.366 at the village level. These values correspond to a highly concentrated market [Justice and Comission, 2010]. Thus, the assumption of price-setting is reasonable, although these establishments would be constrained to some degree by private sector competition.

4.5 Calculation of Profit Measure

The drug inventory data from the vendor survey establishes the choice set that providers may offer mystery shoppers to purchase. The vendor survey contained an extensive collection of prices, costs, and measures for demand for all antimalarial drugs typically in the store's stock. I use this data to create the outcome variable "profit per purchase".

There were an average of 5.3 antimalarial drugs listed on the inventory section of the data, and on average 4.4 drugs listed were currently in stock; 1.83 of the drugs in stock were AL. 96 percent of respondents report their outlet stocking AL, and 90 percent of respondents had AL in the outlet's stock at the time of the drug vendor survey. Despite this extensive range of data, only 423 drug purchased during mystery shopping were able to be linked with their exact cost and selling price information. The remainder either were missing entirely from the survey, or the cost/selling price information were not reported. There are several reasons why. First, no data is available for outlets at which no survey was completed. Second, some respondents either did not know the cost price, or stated that such information was confidential. Third, due to the observed average differences in prices and costs by brand, I only consider exact matches by brand, as opposed to active ingredient. Finally, although it was intended to capture these measures for all drugs that were typically carried, there is likely measurement error and recall bias present, particularly for drugs not in stock at the time of survey.

In order to limit measurement error and non-random missing data, I average unit costs for the brand over the parish. Formally, the measure is:

$$cost_{bp} = \sum_{i=1}^{N} c_{ib} \tag{1}$$

where c is the calculated cost of one full adult dosage in store i of N stores within a given parish p. I then calculate per-unit profit according to the standard formula:

$$profit_{tb} = price_{tb} - cost_{bp} \tag{2}$$

where profit varies at the transaction level t.[38] For the measure *price* for transaction t of brand b, I use both the offer price and the transaction price. The offer price is the first price offered by the vendor before bargaining. In Appendix D, I present additional support for the validity of this measure of per-transaction profits.[39] It should be noted that this measure of cost as in Equation 1 is not only the estimated average per-unit cost, but also the estimated marginal cost for the majority of drugs. Survey data indicate that the majority of vendors have a linear cost structure for antimalarial drugs, although 36 percent report receiving bulk discounts.

5 Conceptual Framework

Dulleck and Kershbamer [2006] present a unifying framework of markets with experts, also known as markets with "credence goods". In purchasing credence goods, customers cannot perfectly assess their utility from the good at the time of purchase, or even after usage. This framework can be used to evaluate in what situations experts are likely to inefficiently provide unnecessary services, lower quality, or price discriminate. As the authors show, the optimal response by experts depends upon whether assumptions regarding customer homogeneity, customer liability protections, and verifiability of the service performed hold.

While powerful, this unifying framework is static. Aside from liability, it does not fully incorporate the penalties experts may face regarding future detection of their strategic behavior. For example, there may be ethical, legal, or social penalties for experts who overcharge, substitute lower quality services, or otherwise are not good at advising purchases. The literature has identified that reputation effects may be an important mechanism that prevents markets from unraveling [Hubbard, 2002, Schneider, 2007, Dranove, 1988]. Providers may not find it optimal to behave strategically if they risk losing future sales from their strategic behavior;

[38] If there are no observations for a given brand in the parish, I then use the average cost of one full adult dosage for that brand in the district, and include a dummy for the imputation.

[39] I use prices from the mystery shopper survey because it is a better measure of the per-unit profit than the average selling price as listed on the drug inventory survey.

in this case, selling a low quality drug. This straightforward intuition, based upon Schneider [2007] is presented formally in Appendix B.

6 Empirical Strategy

My empirical strategy is to compare mean differences in price, options, and service quality between shoppers who recite randomly assigned scripts in the same market. I first test the identification assumption by showing that treatment groups display similar averages of observable characteristics. I evaluate the provider response to customer information on the price, quality, and service quality received. I then test whether the type of information results in different outcomes for customers.

6.1 Estimating Equation

Here I present the main estimating equation, and discuss how standard errors and multiple outcomes hypothesis testing are handled.

$$Y_{st} = \alpha_0 + \alpha_1 AnyInformation_{st} + \gamma_v + \delta' X + \epsilon_{st} \tag{3}$$

where *Any Information* corresponds to whether the shopper either stated malaria, asked for a first-line treatment, or both. Y is the outcome: measures of price, quality, service quality, and other relevant outcomes for transaction t in shop s located within village v. Because there are or the large number of outcome variables, I include as a dependent variable summary indices for related groups of outcomes, following Kling et al. [2007]. This index is the average z-score within a family of outcomes compared to the mean and standard deviation of the control group, and all signs are flipped so as to have the same interpretation. In order to control for unobserved variation across villages, I include γ, a village fixed effect.[40] I include a vector of covariates, X, consisting of shopper, visit order, and patient fixed effects to control for potential omitted variables and absorb residual variation. I cluster standard errors at the shop level to account for any correlation of the error terms within shops with respect to outcome

[40] In order to ease exposition, I present results from a village fixed effect in order to keep a consistent specification throughout the paper and to maximize statistical power.

variables. There are 459 clusters in the analysis sample.[41]

I then differentiate whether providers respond differentially to knowledge of either diagnosis or treatment. I use the following specification:

$$Y_{st} = \beta_0 + \beta_1 KnowOnlyMalaria_{st} + \beta_2 KnowOnlyAL_{st} + \beta_3 KnowMalariaAL_{st} + \gamma_v + \delta' X + \epsilon_{st} \tag{4}$$

KnowOnlyMalaria is a dummy variable for whether or not the shopper was randomly assigned to the treatment group "Know *Malaria*, Ask for Recommendation", *KnowOnlyAL* is a dummy variable for "Ask for Diagnosis, Know *AL*", and *KnowMalariaAL* is a dummy variable for the "Know *Malaria*, Know *AL*" treatment group. Each coefficient measures the average difference in outcome Y between the individual script "treatment" and the "control" script, having no information ("Ask for Diagnosis, Ask for Recommendation"). Therefore, β_1 identifies the effect of giving a shopper only knowledge of the diagnosis (malaria); β_2 identifies the effect of giving a shopper only knowledge of the first-line treatment (AL); β_3 identifies the effect of giving a shopper knowledge of both the diagnosis and the first-line treatment, compared to not having knowledge of either.

I use the script randomly assigned and not the script actually used in all specifications. In the analysis sample, 3 percent of scripts used for purchase differ from the script that was actually used. In Appendix E, I test whether these mistakes are likely to introduce bias into results, and conclude that there is no correlation between reciting a correct script and the actual script or outcomes of interest. However, these mistakes may somewhat attenuate coefficients of interest by introducing measurement error.

6.2 Two Identifying Assumptions

I demonstrate that random assignment was effective at creating four groups that are comparable on average characteristics. The inclusion of village and shopper fixed effects addresses potential concerns of omitted variables bias, and is primarily useful for absorbing residual variation. I also discuss how the experiment was implemented to avoid experimenter or Hawthorne effects.

[41] Future versions of this paper will include an appendix table with the p-value adjustment for multiple outcomes.

6.2.1 Assumption 1: Random Assignment

In order for estimated coefficients of interest to be unbiased, the assigned script needs to be uncorrelated with other omitted variables specific to the transaction. The nature of the design made it difficult to collect characteristics on shops prior to the shopper visits. Instead, I use objective observations and characteristics of the visit to test for systematic differences between treatment groups. These characteristics are unlikely to have been affected by shopper behavior. Evidence that there are no systematic differences between scripts in the analysis sample is presented in Table 4. Appendix Table A4 contains the same table using the full sample of all visits.

In total, 53 percent of visits occurred at drug shops, and 39 percent occurred at clinics. In approximately half of transactions the local language of Runyankole was used, and in approximately one-third of transactions the local language of Luganda was used, reflecting the predominant local languages of the study area. As designed, the patient was the uncle in half of transactions. Overall, 41 percent of shop visits took place over a weekend, and 66 percent of visits took place between 12 and 5pm. Approximately 79 percent of shopkeepers were female, and overall 8 percent of shopkeepers had a baby or small child with them in the shop. In total, 42 percent of shops did not have a name. 59 percent of visits were done by female shoppers, and bargaining resulted in a successful reduction in 59 percent of transactions.

Columns 6 -8 of Table 4 provides supporting evidence that there are no systematic differences with respect to observed or unobserved characteristics between any of the four scripts. P-values from an F-test of mean differences between the four groups demonstrate a significant difference for only a few of the selected variables, using either the cross-sectional variation (Column 6), including a village fixed effect (Column 7), or a village fixed effect and a shopper fixed effects (Column 8). These p-values provide support for the identification assumption that scripts are randomly assigned to visits, and thus estimated coefficients are unbiased. Although there are several statistically significant differences, particularly for establishment type and language used, this imbalance is likely not cause for concern. Some differences would be expected due to chance, and the absolute magnitude of differences is small. Controlling for imbalanced characteristics in regressions does not change point estimates. However, my preferred specification omits these controls, because some coefficients lose significance due to multicollinearity. For example, there is little variation in language within a village.[42]

6.2.2 Assumption 2: Providers React to Information, Not Experiment

A second condition that must hold is that, from the perspective of the shopkeeper, all shoppers must be perceived as identical on average except with respect to the randomly assigned script. Available evidence does not suggest this is a significant source of bias. First, shoppers were extensively trained on all aspects of protocol, in both the classroom and in pilot work, and the protocol was reviewed every morning.[43] Similarly,the protocol was carefully implemented to limit behavior that would be out of the ordinary. For example, shoppers practiced approaching the shop and a strict dress code was enforced so as to limit any signals of wealth, such as cell phones or jewelry. In addition, I include a shopper fixed effect to control for any characteristics specific to a shopper. Responses on the vendor survey suggest that these precautions were effective at limiting provider suspicion. Only eleven percent of respondents reported on the vendor survey "yes", they had ever been visited by a mystery shopper. Only 3 percent of respondents identified a time period of where the reported mystery shopping could have been associated with our study.

6.3 Selection bias on purchases

One concern with the analyses of prices and quality is that I do not observe transaction prices from visits where no drug was purchased, thus potentially introducing a selection bias for those specifications. I account for this potential problems by showing that whether the transaction is part of the analysis sample is uncorrelated with the randomly assigned script. Second, I sign the selection bias term as negative. Third I construct Lee bounds [Lee, 2009] on point estimates from models that are conditional on making a purchase and being tested as a robustness check; estimates are in Appendix tables.

Overall, 96 percent of attempts to purchase a drug resulted in the shopper interacting with a shopkeeper. Unsuccessful visits were typically because the shop was either temporarily closed (N=60). Of successful visits, 92 percent resulted in a purchase. In 3.3 percent of visits

[42]The randomization was implemented with a parish fixed effect, and thus there may be a concern that random assignment is only valid conditional on a parish fixed effect. Because parish is collinear with village, comparing the p-values in the cross section with specifications inclusive of fixed effects is equivalent to demonstrating that the stratification cells are mostly relevant for absorbing residual variation.

[43]Details of training are in Appendix F.

there was no drug sale due to refusal to sell without seeing the patient (N=34) and during 4.6 percent of visits (N=47) the vendor was out of stock.[44] Results in Panel A of Table 5 show that having any information does not change the likelihood of reporting that a drug is out of stock, being denied a sale, making a purchase, or the types of drug purchased.

Although the scripts do not differ in the report of whether the outlet has any drug in stock, there are slight differences in being denied a sale across the treatment groups. Shoppers indicating the knowledge of both malaria and appropriate treatment are 3.6 percentage points more likely to be denied a sale than the Control group. Although the likelihood of buying a particular type of drug is uncorrelated with the randomly assigned script, customers knowing both malaria and AL score 0.08 standard deviations less likely on the purchase index, significant at the 10 percent level.[45]

Appendix Table A2 shows that clinics and outlets which charge consultation fees, are the most significant predictors of whether shopper made a purchase. Consultation fees are approximately double the cost of treatment (which the customer would still need to pay), so there are substantially higher profits from customers who return with the patient at those establishments. Because clinics generally have higher prices than drug shops or pharmacies, these patterns suggest a negative selection bias term.

7 Results on the Provider Response to Customer Information

I present several sets of results suggesting that providers charge lower prices and lower quality when customers state more information.

7.1 Prices

There is suggestive evidence that increased customer information results in an economically significant decrease in price. In Panel A of Table 6, I present estimates of the effect of any information on the price paid. Although some specifications lack significance at conventional

[44] According to official WHO guidelines, all of these purchases should have been denied. The guidelines state that adults should only be given antimalarial drugs if the patient tests positive for malaria according to a blood test, either rapid diagnostic or blood microscopy.

[45] Results are similar in the analysis sample. Although there is no difference for the purchase index across scripts, shoppers knowing only malaria are 4.4 percentage points more likely to buy SP. See Appendix Table A3 for additional details.

levels, the effect of having information results in a price decrease between \$0.13-\$0.18. In the full sample of all purchased drugs, customers with any information are charged \$0.13, although this value is not significantly different from zero (p-value = 0.177).[46]

Restricting the sample to those drugs which could be tested has the effect of reducing some of the variance in the price distribution. Thus I am able to detect statistically significant impacts among the analysis sample.[47] In column 2, I show that that providers charge customers with any information approximately \$0.18 less. This effect is approximately the same whether the price is measured as of the offer or the final transaction price. Although the experimental design held constant the shopper's drug preferences, the data collected can be used to assess what would have happened if instead the shopper had bought the recommended option. Column (3) shows that if the resulted shoppers had instead bought the recommended option, the differences between scripts would have been even larger, at \$0.27. These results are robust to both a log specification and the multiple outcomes index. Shoppers with any information are offered a price that is 5 percent lower than shoppers with no information. The aggregated index from these measures indicates that customers with any type of information have a decreased average price index of 0.081 standard deviations.

Panel B shows that, in the analysis sample, the provider response does not differ by the type of information. In the analysis sample, shoppers who only know that the patient has malaria are charged \$0.23 less, and shoppers who know both diagnosis and appropriate treatment are charged \$0.19 less. Results are approximately of the same magnitude for the price paid. These price differences would likely have become substantially larger if instead the shopper had purchased the recommended option; shoppers knowing both diagnosis and treatment would have paid nearly \$0.38 less. Using the outcome of log of the offer price shows that these results are robust to a log specification, although slightly noisier. The effect of information on the price index is consistently negative and approximately -0.07 to -0.09 standard deviations, all significant at the 5 percent level. Results are robust to the inclusion of day fixed effects, day of week fixed effects, and drug type purchased. However, I caution that results are not generally

[46]Results similarly show suggestive evidence, but no statistically significant effects for prices using either a level or a log specification. However, the effect of information on the price paid is significant when controlling for the type of drug purchased. See Appendix Table A7.

[47]In particular, dropping either the other high-quality antimalarials or the quinine drug types reduces variation sufficiently to detect statistical significance. For example, other high-quality antimalarials are priced approximately \$2.18 more than AL.

robust to additional procedures to accommodate outliers, such as trimming or winsorizing (not shown). Therefore, observed large responses among some providers to information are an important component of the average effect on prices charged.

The calculation of Lee Bounds in Appendix Table A8 generally supports the interpretation that information decreased price. Although the upper bounds are not always statistically significant, the bounded estimates are consistently negative for all outcome variables. In addition, the price index (which increases statistical power) shows a negative upper and lower Lee Bound.

7.2 Profits

In Table 7, I test whether charging lower prices translates into lower profits. I find that customers with more information are lower profit-margin customers for vendors.[48] Columns 1 and 3 calculate profits using the offer price; Columns 2 and 4 calculates profits using the transaction price paid. Panel A shows that by any measure, vendor marginal profits off of the transaction decrease by approximately \$0.22 when customers have some information regarding diagnosis or treatment. Specifically, Column 1 of Panel B shows that providing a shopper knowledge of diagnosis (malaria) lowers profits by \$0.22, and providing shoppers both types of information lowers profits by \$0.27. There is a substantial reduction in profits when customers know either the diagnosis or the recommendation. Results are robust to using the price paid instead of the offer price. Using the sample of purchases, as opposed to all visits, highlights that the effect of customer information on profits is not driven by whether or not a drug was purchased. Although estimates are slightly noisier, potentially due to fewer observations, results are similar. These coefficients are similar in magnitude to the coefficients on price, and suggest that the lower profits are not driven by switching across differently cost brands, but rather reductions in price. This interpretation is supported by the fact that average costs by brand at the parish level do not differ by script (not shown).

[48] Visits in which the drug brand could not be identified, or where cost data was not available in the sample, are excluded (N=32).

7.3 Add-Ons

In addition to antimalarial drugs, outlets also commonly sell other products for the treatment of malaria symptoms, such as fever reducers, headache medicine, vitamins, and even antibiotics. Results of Table 8 indicate that providers also potentially lose profits on shoppers with more information by not offering them additional products. Panel A shows that providers offer 0.092 fewer options to shoppers who know either the diagnosis or treatment. Similarly, customers with any type of information are 13.3 percentage points less likely to offer additional products to relieve the symptoms of malaria. Overall, providers substantially decrease the menu of options presented by 0.44 standard deviations of the menu index.

Panel B shows that as shoppers present more information, providers are more likely to decrease additional options. Shoppers who ask for a specific treatment are offered between 0.13-0.16 fewer antimalarial drug options. Shoppers who know the disease is malaria are 9 percentage points less likely to be offered an additional product. Shoppers knowing only the first line treatment are 13 percentage points less likely to offered an additional product. Shoppers with both types of knowledge are 17.7 percentage points less likely to be offered an additional product. Therefore, in addition to the main channel of decreased profits through lower prices, shoppers with information are substantially less likely to be offered additional products and services.

7.4 Drug Quality

In this section, I consider the effect of information on both observable and unobservable quality. I consider observable measures of drug quality to be correct dosages and diverted drugs, those with public sector markings. I consider unobservable measures of quality to be counterfeit to substandard medicines. I find that increased customer information is increases observable quality, but decreases actual drug quality.

In Table 9, I examine whether vendors respond to customers with different levels of information by adjusting drug quality. I first consider two measures of quality that would be observable to the customer at the time of purchase: whether the dosage had the correct number of tablets, and whether the drug was diverted. If one considers these as “observable” measures of quality, drug quality improves. Shoppers presenting any information regarding diagnosis or treatment are 4 percentage points more likely to receive the correct number of tablets, and 3.9 percentage points less likely to buy a drug with government markings. The coefficients do not differ substantially in magnitude by the type of information presented for either dependent variable.

Columns 3 -5 presents estimates from the spectrometry analysis. These measures of drug quality that are likely not observable to a shopper at the time of purchase. Whether or not shopper information is correlated with drug quality is dependent upon the measure of quality used. Although there is no difference in the likelihood of purchasing a counterfeit drug between shoppers with different levels of information, there is a relatively large and significant difference in the likelihood of buying a substandard drug. Shoppers knowing either the diagnosis or the treatment are 3.4 percentage points more likely to buy a substandard drug. Shoppers knowing that the patient has malaria are 3 percentage points more likely to buy a substandard drug, and shoppers knowing both malaria and the first-line treatment are 5.4 percentage points more likely to be a substandard drug. Results are robust to considering whether the outcome variable is the fraction of drugs within the stock is substandard, and also the z-score index of drug quality. However, I caution that these results are based off of a small proportion of the sample.

Key to this interpretation is that at least a subset of vendors know the quality of their stock. Available evidence supports that some proportion of vendors do know whether drugs are of high or low quality, and whether the drugs come from public sector facilities. For example, shoppers stating any information are 3.9 percentage points more likely to report vendors picked the dispensed drug from the back of the outlet, or otherwise out of sight of the customer. There is similarly a positive, though insignificant relationship between picking from the back and whether the drug had public sector markings, was counterfeit, or substandard. In addition, many of the drugs with public sector markings were bent to make the stamp less noticeable, or the stamp was partly rubbed off.[49]

The calculation of Lee Bounds in Appendix Table A8 shows that these estimate are generally robust, and not the result of sample selection. Correct dosage, diverted drug, and fraction substandard have significant upper and lower bounds. Although, the lower bound on whether

[49] In Atukunda and Fitzpatrick [2014], I also do a list randomization exercise following Karlan and Zinman [2011] and show that at least some subset of vendors know drug quality.

the drug was substandard is small and insignificant, it is still positive. However, the drug quality index is inconclusive, as the upper bound switches sign.

7.5 Service Quality

The quality of healthcare by providers is low in many developing countries [Das and Hammer, 2014]. Providers generally exert low levels of effort with respect to both diagnosis or treatment, compared to what their actual level of knowledge is [Das et al., 2013]. Similarly, in Uganda, poor service quality is commonly cited as a reason why individuals do not seek treatment in the free public sector [Xu et al., 2006].

In Table 10, I consider two different measures of "service quality". Following Das et al. [2013], I test whether providers abide by a "checklist" of proper behavior in relation to the rational use of medicines. According to official guidelines, providers should not dispense medicines on symptomatic basis alone; the patient should first take a malaria test. If tests are not available, then the provider should ask for additional symptoms to rule out other types of illnesses. I consider whether providers alter any of these behaviors in response to the scripts. Second, I test whether subjective measures of good customer service improve. Existing evidence from both developed and developing countries that patients care not only about whether health outcomes improve, but also the process through which decisions are made [Kroeger and Hernandez, 2003, Jennings et al., 2005, Kruk and Freedman, 2008]. Patients value adequate time with providers, being respected, and other aspects akin to "bedside manner". I apply those principles to the antimalarial health market. I test whether the shoppers felt that they were given adequate attention, whether they felt like the provider explained all options, or whether the provider was rated as very friendly. Results suggest that providers respond to increased shopper information by exerting lower effort, and decreasing service quality.

Shoppers knowing either the diagnosis or appropriate treatment are not more likely to have doubts expressed to them regarding whether the patient truly had malaria. However, they are 6.8 percentage points less likely to be advised to have the patient take a malaria test, and 4.7 percentage points less likely to report the provider asked any questions regarding the patient's health. Shoppers with any information are 11.9 percentage points less likely to report that they were given enough time for their purchase and are 8.5 percentage points less likely to feel that all of their options were explained to them. Other point estimates for outcome variables of whether the vendor asked health questions, whether the vendor was rated as "very friendly" is negative, although insignificant. Amassing these variables into an index, shoppers with information rate vendors as 0.126 lower standard deviations of service quality.

The pattern of coefficients in Panel B indicates that the more information that the customer presents to the vendor at the time of purchase, the less likely it is that providers adhere to the rational use of medicines. Customers who both know the disease is malaria, and ask for the first-line treatment are 8.2 percentage points less likely to report that the provider expressed doubts and 15.8 percentage points less likely to report that the provider advised the patient to take a malaria test. They are also 9.7 percentage points to report that the vendor asked health questions about the patient. There is no difference in outcomes for shoppers who know only the diagnosis or appropriate treatment.

Shoppers reciting scripts where they know either the diagnosis or appropriate treatment also rate the providers as giving them lower service quality. Customers knowing either the diagnosis or appropriate treatment are 11.9 percentage points less likely to report that the provider gave them enough time and 8.5 percentage points less likely to report that all options were explained to them. Panel B shows that these measures of low service quality are found among each treatment group. The effect of information on whether the provider gave enough time ranges from 5.6 - 18.6 percentage points. The effect of information on whether the provider explained all options ranges from 7.2-10.4 percentage points. Finally, shoppers who know only the first-line treatment are 5 percentage points less likely to rate the provider as very friendly. There is also a consistent negative effect on the service quality index for all treatment groups. Results are robust to a wide range of specifications and samples.

8 Mechanisms: Reputation Effects and the Value of Service Quality

Although a standard model would predict that prices fall as information asymmetries are decreased– through decreasing search costs– it is less clear why decreasing information asymmetries also lowers both service and drug quality. Furthermore, it is unclear why a given customer would not recognize that there are substantial price decreases from simply stating the patient has malaria. In this section, I use two approaches to identify plausible mechanisms driving the experimental results. Each approach highlights a different mechanism. First, I analyze additional survey data from real customers. The results suggests information may signal additional characteristics regarding consumer demand to providers. In particular, providers may believe customers with more information are less likely to return to the outlet and are less likely to value good service. Because there are lower penalties from detection from consumers who are less likely to return anyway, providers may strategically allocate low quality drugs to customers where the reputation incentives are weaker. Second, I estimate hedonic regressions of price on quality from the experimental data to show there is a service quality "premium".

8.1 Evidence from Real Customers

One drawback of the experimental data is that I cannot explicitly document what a given provider believes about customers with different levels of information. For example, providers may believe that customers with different levels of information regarding the disease may also differ in characteristics correlated with individual demand. To providers, information may also signal their likelihood of using preventive measures, wealth, or their likelihood of returning to the outlet. Therefore, I use additional data collected from real customers to estimate what types of characteristics are correlated with information. The assumption underlying this analysis is that characteristics observable to the econometrician would also be known to the provider.

I divide real customers who purchased antimalarial drugs into two groups: customers with information, and those without information. Real customers who report knowing either the disease (malaria) or a specific treatment are classified as having information, to mimic the experimental design. Real customers who report asking for both a diagnosis and a product recommendation are classified as not having information. This divides the sample roughly in half; 52 percent of the customers purchasing antimalarial drugs report asking for both a diagnosis and recommendation.

First, I analyze whether the correlation of information with transaction outcomes is of the same sign to that found in the experiment. Results in Panel A of Table 11 show that customers with information do not differ in the likelihood of purchasing AL, but they are substantially less likely to report the patient take a malaria test. They are less likely to buy an additional product, spend less money for the product, and have a lower total bill.[50] Although I cannot separate consumer preferences from provider behavior, the net result of the transaction is similar to the experimental results with a negative omitted variables bias. Therefore, if provider beliefs explain the results, beliefs need to be negatively correlated with information and positively correlated with price, or vice versa.

Second, I look at potential demographic characteristics associated with customer information to test if providers lower quality and lower price on the basis of observable characteristics. Results in Panel B show that there are only two characteristics with statistically significant correlations with information: years of education and whether or not the customer was a repeat customer. Customers with no information are 15 percentage points more likely to be a repeat customer than customers with more information, significant at the 1 percent level. Other characteristics suggestive of other mechanisms do not appear to be evident in the data. Other testable explanations include community members as compared to non-community members (proxies by distance to outlet); the likelihood of preventive treatment (usage of a mosquito net and malaria literacy score); traditional price discrimination on the basis of differential demand elasticities due to income or household characteristics (borrowed money, income, or children in household); taste-based discrimination on the basis of gender (female). These relationships are not to be considered causal. However, they are suggestive that providers may also recognize that customers with less information are more likely to return. This is in line with previous research that those with less knowledge regarding health are more likely to seek treatment [Ingham and Miller, 1983]. Therefore, it may be rational to give substandard medicines to customers where the potential reputation costs are lower.

Finally, I adapt the specification in Equation 4 to examine the robustness of this interpretation. Specifically, I examine the linkage between information and the value of customer service. Real customers were asked on the survey where they typically shop, and why they choose this particular store for their purchase today.

$$Y_{st} = \lambda_0 + \lambda_1 AnyInformation_{st} + \gamma_v + \psi' X + \mu_{st} \tag{5}$$

where $AnyInformation$ is a dummy variable indicating that the real customer either

[50] Note that because drugs purchased from real customers were not tested, I am unable to directly test the correlation of drug quality with real customer characteristics.

knew their diagnosis or asked for the specific product that they wanted.[51] I test whether information is correlated with the value placed upon good service, controlling for whether the patient was an adult, income, years of education, and village fixed effects. Results in Table 12 show that customers with relatively more information are less likely to report a variety of customer service measure as important to choosing that store for their purchase.[52] Customers with information are 23.6 percentage points less likely to cite customer care as a reason for choosing that outlet for their purchase; 11 percentage points less likely to cite knowledgeable staff; and 18 percentage points less likely to cite fast service as a reason. Other reasons for choosing the outlet– cheap prices, convenience/distance, or good product selection– do not differ between customers with more or less information. Therefore, it seems that, in addition to their likelihood of returning, value of good service seems to be driving the experimental results.

8.2 Importance of Service: Hedonic Models

Das et al. [2013] find that customers pay for higher quality private sector providers even when free services are available, because service quality is a valued attribute of the good. The effect of customer information on service quality may therefore reflect the market valuation of good service. In order to investigate the relationship between price and service quality, I return to the experimental data. Using the data resulting from the experimental analysis, I estimate hedonic regressions:

$$PricePaid_{st} = \zeta_0 + \zeta_1 ServiceQuality_{st} + \zeta_2 DrugQuality_{st}\gamma_v + \chi' X + \epsilon_{st} \tag{6}$$

Results in Table 13 support the interpretation that providers increase the price charged based upon the exert/service quality that they give. For each additional standard deviation of the service quality index, the price paid increases by \$0.36. This relationship is pictured graphically in Figure 6. The service quality index is significantly and positive correlated with the price paid, although measures of drug quality are not correlated with the price paid. This makes sense, because service quality is observable; as an unobservable measure of quality, drug quality cannot adequately be priced into the price of the good. This finding is robust to

[51] I do not differentiate whether they ask for AL specifically, or whether they asked for a different drug.
[52] Note that multiple responses were allowed.

controlling for drug fixed effects, and also a log price specification. The hedonic regressions support the interpretation that service quality is a valued attribute of the good. Therefore, the market price reflects that the marginal customer positively values this attribute, increasing prices as service quality increases. Individuals with less information appear more willing to pay for service quality. This intuition explains not only the experimental results but also informs why the majority of customers continue to ask for provider opinions, even though there are substantial price reductions. If price falls as the expense of good service, customers may simply not find it optimal to invest in information.

8.3 Policy Implications

The finding that information could potentially reduce price but may also reduces quality does not imply that individuals should be prevented from learning information about their purchases. My results suggest that information campaigns and empowering customers regarding their purchases would likely be a relatively low-cost intervention to reduce prices. In situations where price is the primary barrier to utilization, my results suggest that an individual would be charged approximately 5.6 percent less: a substantial decrease. However, if there are such large gains from acquiring simple information, it is surprising more of the poor do not appear to do so. Similar to recent work in India by Das and Hammer [2014] I find that uninformed customers have a higher valuation of quality. Therefore, it makes sense that uninformed customers do not find it optimal to invest in information if the result is lower service quality. For individuals who strongly value service quality from their health provider, the net welfare gain from increased information may be small.

From a broader policy perspective, this study provides further evidence that healthcare providers do profit-maximize, and are susceptible to the same issues of agency as in other markets with experts. Therefore, it is unclear whether the most efficient way to distribute essential medicines is to sell them through an unregulated private sector. Whether the market operates efficiently is particularly relevant when the majority of consumers lack necessary information regarding health purchases. Although the over-utilization of antimalarial drugs is typically attributed to customer misinformation, these data suggest that supply-side incentives may also contribute to over-utilization of treatment and (eventually) drug resistance. Therefore, information should be used in conjunction with other policies in order to ensure that quality does not decline, to make subsidies more effective.

9 Conclusion

As the private sector continues to be a central mechanism for the distribution of essential medicines, understanding how agency problems affect prices and quality can have important implications for both health and economic development. Providers have a large financial incentive to increase sales, there are few institutional constraints on price and supplier behavior, and there are low levels of customer information regarding malaria and treatment. One potential solution to agency problems is to decrease information asymmetries.

In this paper, I conduct a randomized audit study in the Ugandan antimalarial drug market to assess the impact of customer information on the price charged and quality received. My findings suggest that there is a substantial reduction on prices, drug quality, and service quality when customers exhibit information regarding their purchases. In my preferred specification, orices for the same drug fall by approximately \$0.18; the price differential between customers with any information and no information and would have increased to approximately \$0.27 if shoppers had purchased the treatment recommended by the provider. However, effects on price are noisy and at times insignificant. Counterintuitively, I find that drug quality *falls* by 3.4 percentage points. I also find that substantial decreases in service quality.

I interpret these results through a framework where customers have several characteristics that characterize their demand. Although information affects the price that a given customer is willing to accept, customers also value service quality. Customers also differ in their likelihood of returning to the same outlet. In this manner, providers strategically allocate low quality drugs to customers that they would be unlikely to lose profits from in the future, were their behavior to be detected. I bolster this interpretation with evidence from real customers, as well as hedonic price regressions indicating that there is a positive correlation between service quality and price, and a negative correlation between information and valuing service quality.

Results suggest that more research needs to be done on low quality medicines. Clear guidelines need to be enacted to ensure continued access to high-quality generics while simultaneously eliminating substandard medicines. Results suggest that although counterfeit drugs are relatively common– 17.1 percent– substandard drugs are relatively rare, at only 3.4

percent. From a regulatory perspective, the current control measures in place in Uganda seem to be effective at ensuring access to effective anti-malarial medicines. However, if regulators believe that counterfeit (although likely effective) drugs are also a serious problem, then substantial additional resources may be necessary. Although determining whether substandard or counterfeit drugs are of bigger policy concern is beyond the scope of this paper, results suggest that there is a substantial distinction between the two measures that future research should incorporate.

This paper is particularly relevant from a public policy perspective. The problems of the public sector healthcare service delivery continue to impede access to essential medicines, particularly for the poor. As a result, the private sector has become an important mechanism for accessing healthcare. Private sector providers give better service quality and are more accessible. However, the same profit-seeking motivations can also exacerbate issues of consumer inequity and the over-utilization of healthcare due to provider agency problems. Although informational asymmetries cannot entirely be eliminated in the market for healthcare, I demonstrate in this paper that vendors respond differently to customers with different types of information. If more customers presented an increased awareness of malaria diagnoses or first-line treatment, then results indicate that market prices would fall. Unfortunately, service quality and drug quality would also fall as well. As a result, individuals may not benefit as much from lower prices and information levels may remain low. Therefore, information should not be a sole strategy to improve consumer welfare, but used in conjunction with other interventions to improve access to high quality healthcare worldwide.

Figure 1: Project Timeline

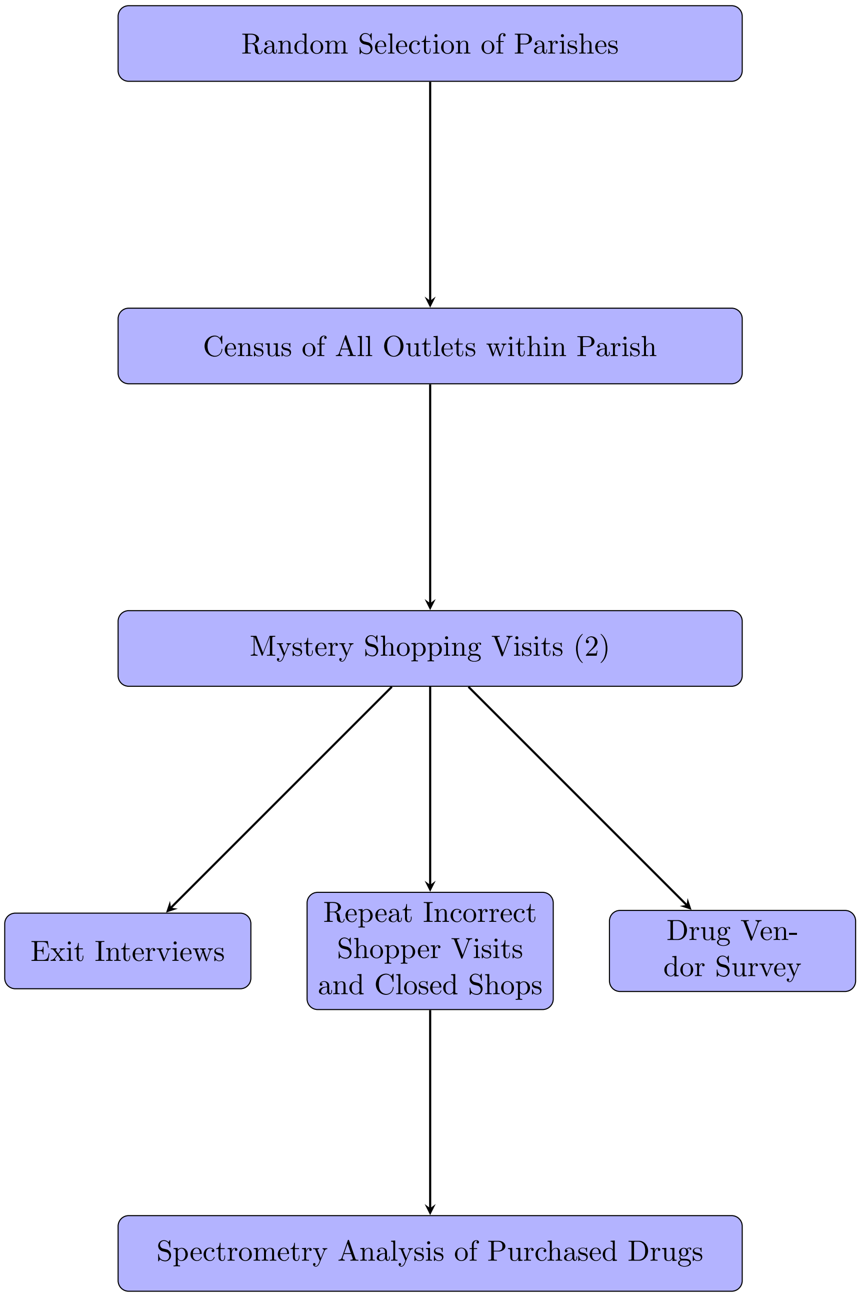


Figure 2: Experimental Protocol

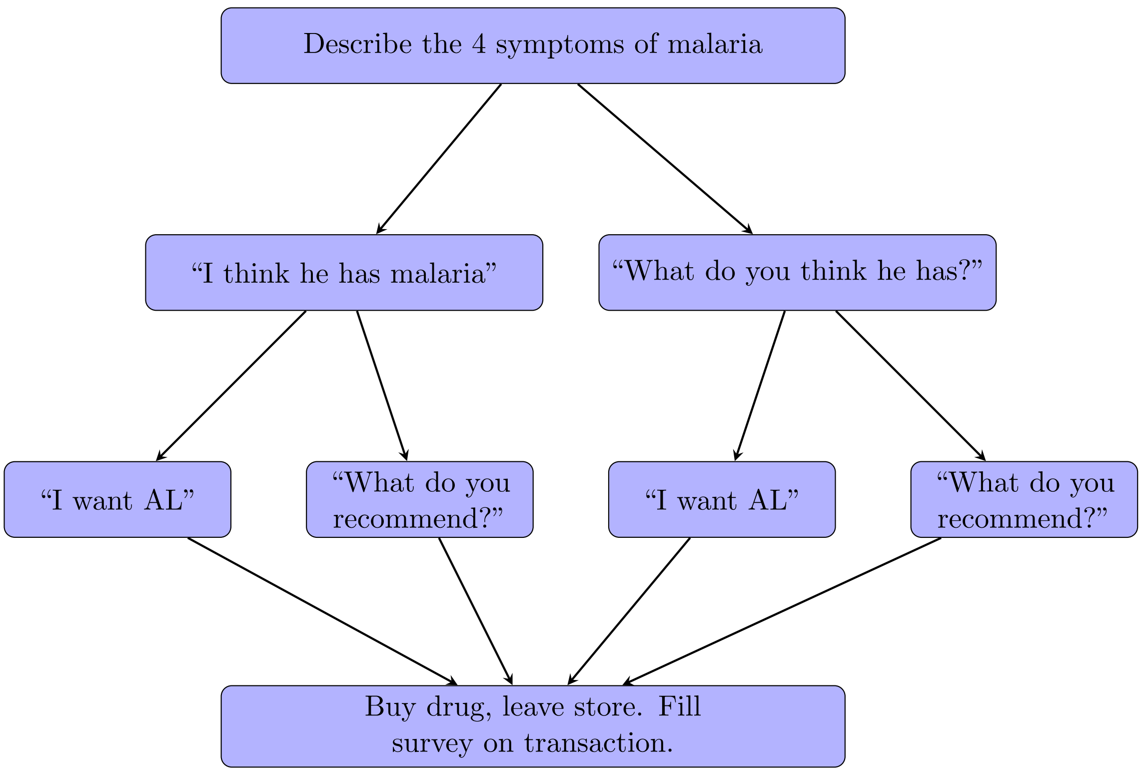
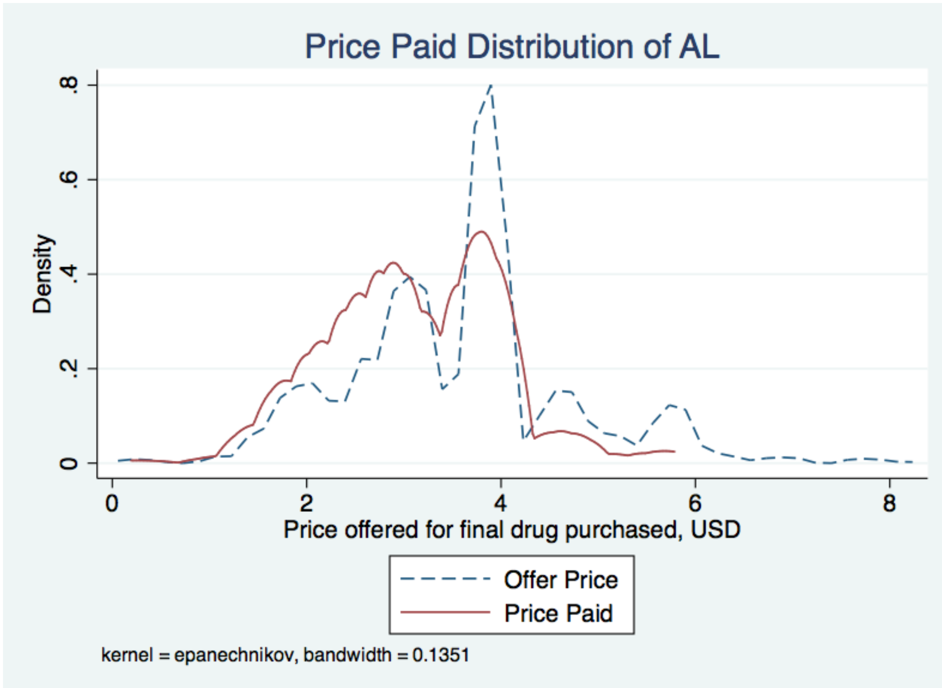
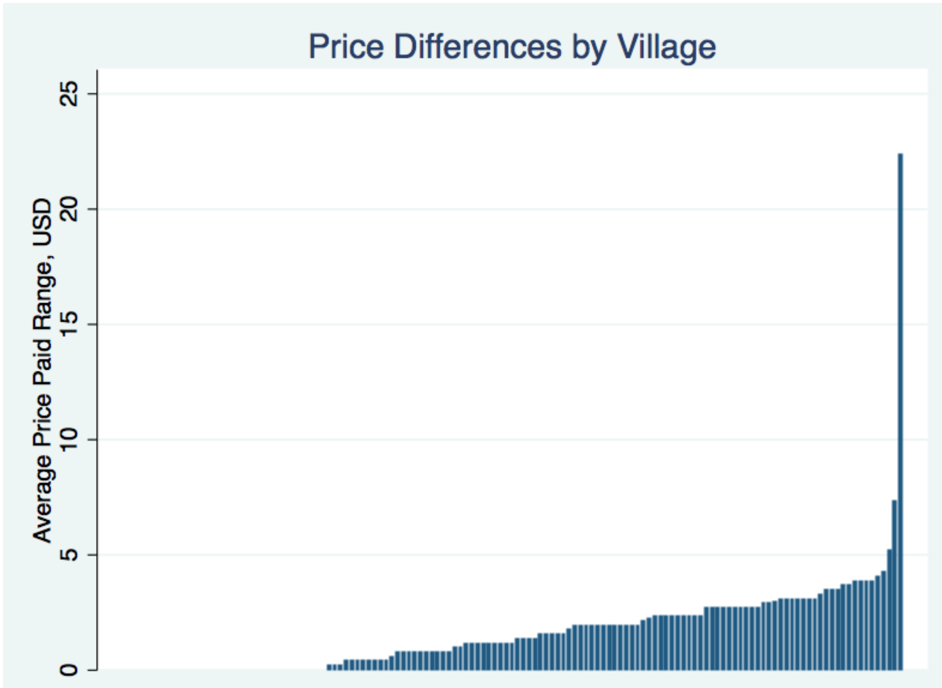


Figure 3: Price Distribution



Notes: Above is the graph of the offer (pre-bargaining) and transaction prices (post-bargaining) for the final drug purchased, in USD. The exchange rate is $1=2593 UGX. The sample is restricted to purchases of AL, and excludes high outliers values of the distribution, greater than $10.00 (N=802).

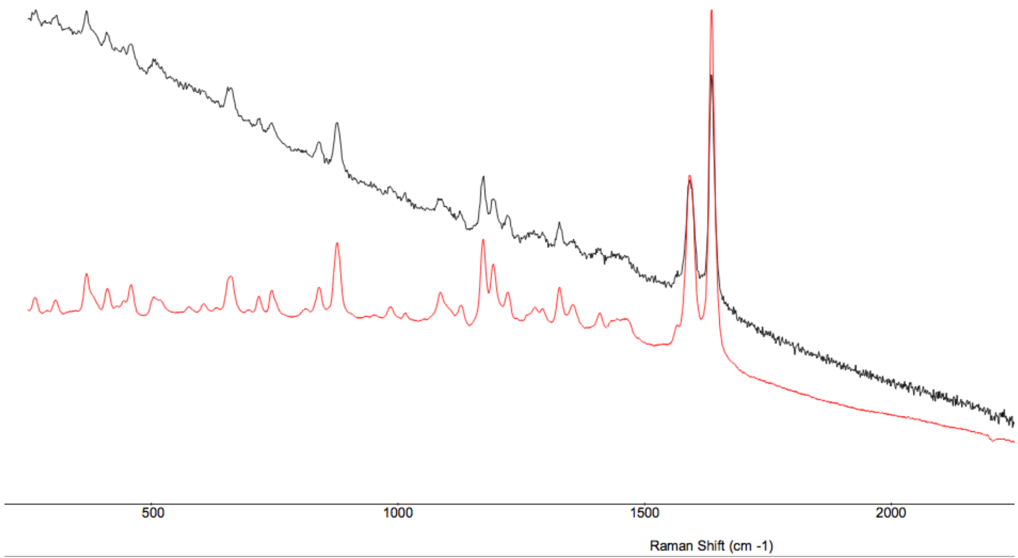
Figure 4: Price Dispersion



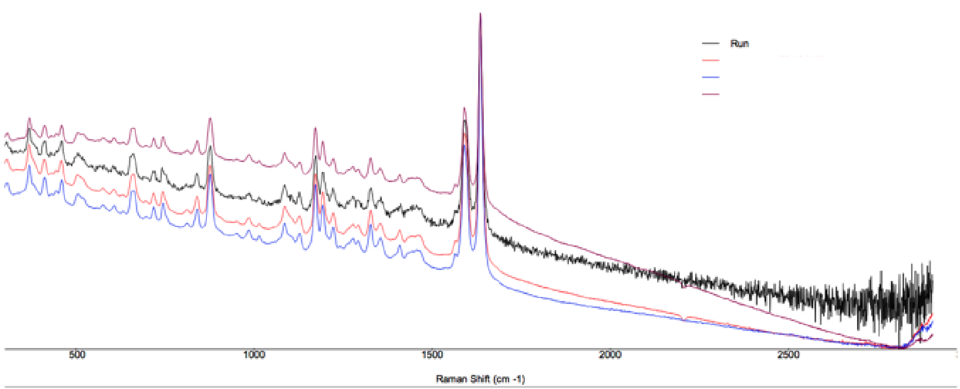
Notes: Above is the graph of the price range within a village for the final drug purchased among all drugs purchased. Each bar is a separate village. The price is the final price paid, measured in USD. The exchange rate is $1=2593 UGX.

Figure 5: Demonstration of A Raman Spectrometry Scan

Panel A: A Counterfeit Scan

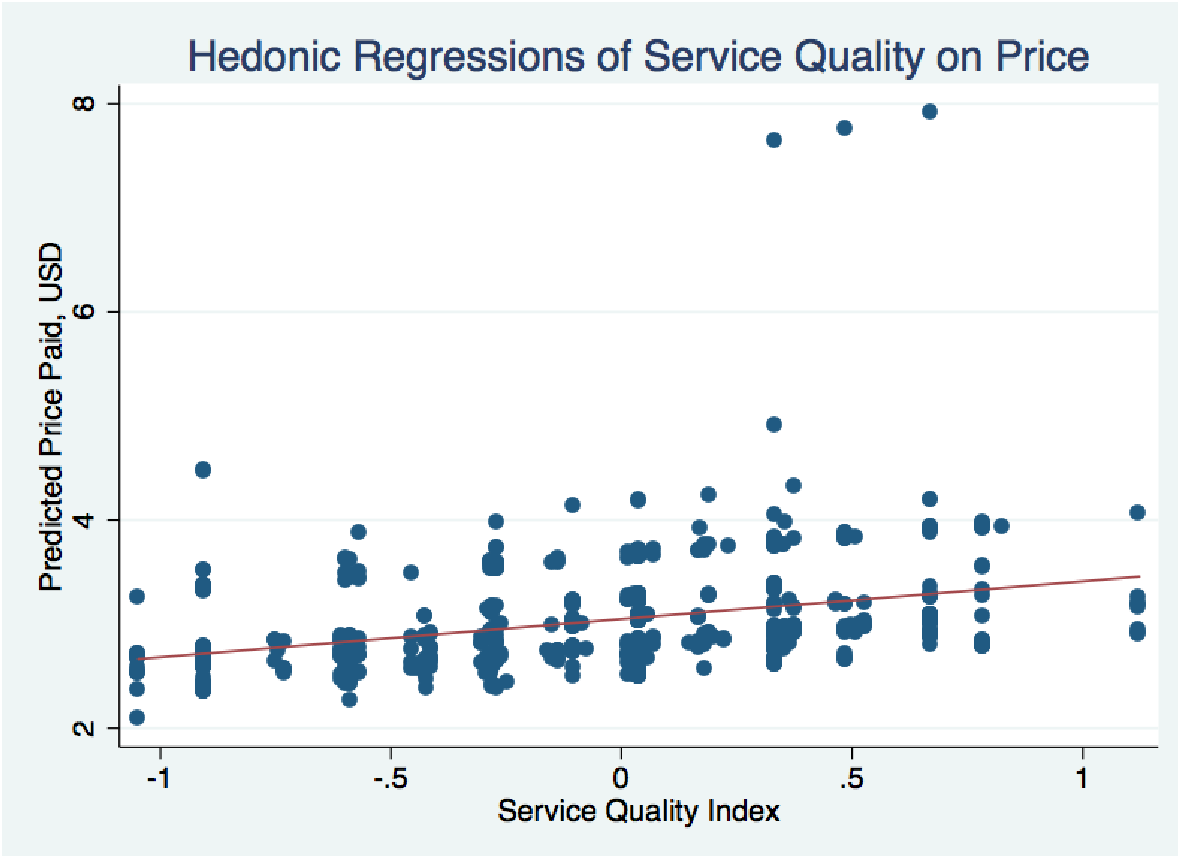


Panel B: Discovery Mode- Counterfeit, But Not Substandard



Notes: Raman spectroscopy works by blasting a molecule with an intense beam of light that causes the molecule's electrons to scatter in a specific fashion unique to the molecule. Therefore, if two spectra are the same, then the two molecules are likely the same. Because the analysis is specific to the molecule, the test is brand specific, and cannot distinguish whether failures are due to differences in active or nonactive ingredients. Above is a picture of the Raman spectra from a sample of AL that was classified as "Counterfeit but not substandard". In both panels, the black line is the Raman spectrum of the purchased tablet. In Panel A, the spectrum is compared against the red line, the spectrum corresponding to the brand on the purchased drug label. These spectra were too different and therefore are not considered matches. In Panel B, the spectrum is compared against the spectrum of all other brands. The purchased tablet does match the spectra of several other brands within the library. Thus, it is not considered substandard.

Figure 6: Hedonic Regression



Notes: Above are hedonic regressions of the effect on the service quality index on predicted price paid. Prices are in USD. $1=2593 UGX. Service quality index is an index created from the z-scores of the following variables: whether the vendor gave the shopper enough time to ask questions, whether the shopper felt as if the vendor explained all of their options, whether the vendor advised the patient to take a malaria test, whether the vendor was rated as very friendly, unfriendly, whether the vendor expressed doubts about the patient's diagnosis. Regressions include shopper, patient, visit order, and village fixed effects. The sample is all visits that were purchased and testing could be done (N=879).

Table 1: Script Distribution and Study Design

	Ask for Diagnosis	Know Malaria
Ask for a Recommendation	Control 0.261 N = 230	Treatment 1: Know Only Malaria 0.248 N=218
Know AL	Treatment 2: Know Only AL 0.250 N = 220	Treatment 3: Know Malaria & AL 0.240 N = 211
TOTAL	450	429

Notes: Above is the realized marginal distribution of scripts that were randomly assigned to shoppers in the analysis sample. N=879. Each cell was designed to have an equal probability of selection.

Table 2: Summary Statistics of Provider Survey

Panel A: Vendor Characteristics	Average
Age	30.14
Male	0.23
Born in this parish	0.089
Qualified person	0.360
Years of Experience as Vendor/Pharmacist	6.190
Score on Malaria Transmission Test	0.808
Knows firstline treatment	0.844
Correct protocol for AL	0.282
Panel B: Outlet and Customer Characteristics	
Number of Customers	21.780
Number of Customers Seeking Malaria Treatment	6.140
Percent Customers Know by Name	0.428
Percent of Customers That Ask for Advice on What to Purchase	0.647
Percent of Customers that Ask for a Diagnosis	0.659
Outlet tests for malaria	0.531
Outlet has beds to treat patients	0.468
Charge Consultation Fee	0.142
Monthly Profits (USD), Median	77.13
Number of Employees	2.360
Visited by NDA Regulator in past 6 months	0.716
HH Index Measure of Market Concentration (Village Level)	0.366
Number of Outlets Within Walking Distance	9.980

Notes: Summary statistics from the vendor survey (N=451). "Qualified person" is a dummy variable indicating whether the respondent had the minimum educational and experience qualifications to operate and/or dispense medicines at a drug shop. "Score on Malaria Transmission Test" is the percentage correct of six questions on malaria transmission. "Firstline treatment" is a dummy variable for whether the respondent correctly stated the recommended firstline treatment for uncomplicated malaria (AL). "Correct protocol" indicates whether the respondent knew the correct schedule for a full dosage of AL. "Beliefs on percentage of fake drugs in parish" are the stated percentage of drugs that the respondent believed were fake/counterfeit in their parish. "Number of customers per day" and "Number of customers seeking malaria treatment per day" refer to the total number of customers who visited the outlet the previous day. "Percent of Customers..." refers to the number of customers on an average day. "Whether the outlet tests for malaria" is a dummy variable for whether the outlet either does blood slide testing, RDT testing (including sales only), or both. "Charge consultation fee" is a dummy variable for whether the outlet ever charged consultation fees for diagnostic services. "Monthly profits" is measured in US dollars, and is the stated value of profits from the establishments (sales - costs) over the previous month.The conversion rate is approximately $1=2593 UGX."HH Index" is the Herfindahl-Hirschman measure of market concentration, which is the percentage of customers at that establishment in the previous day divided by the total number of customers at all establishments within the village the previous day. 'Number of outlets within walking distance" is the number of private sector outlets with a 15 minute walking radius from that store, and includes the respondent's outlet.

Table 3: Summary Statistics of Drug Prices and Costs

	N	Percent of Total	Average Price (UGX)	Average Price (USD)	Average Cost (USD)
Panel A: All Active Ingredients	(1)	(2)	(3)	(4)	(5)
AL	806	0.86	8275	3.19	1.28
Quinine	34	0.04	6429	2.48	1.19
SP	79	0.09	2915	1.12	0.59
Other High Quality	7	0.08	12857	4.96	4.16
Other	7	0.08	4071	1.52	0.71
TOTAL	933	1.00	7757	2.99	1.25
Panel B: AL Sample, by Brand	(1)	(2)	(3)	(4)	(5)
Brand A	112	0.14	7393	2.85	1.15
Brand B	253	0.31	7879	3.04	1.27
Brand C	150	0.19	9690	3.74	1.29
Brand D	38	0.05	8144	3.14	1.35
Brand E	35	0.04	10014	3.86	1.87
Brand F	208	0.26	7889	3.04	1.24
Brand G	1	0.00	10000	3.86	–
Brand H (mixed)	9	0.01	9333	3.60	–
TOTAL	806	1.00	8275	3.19	1.28

Notes: Above are summary statistics of the transaction price by type of active ingredient (Panel A) and by brand (Panel B). All are simple means from a cross-section. The active ingredients relevant to the study include artemether-lumefantrine (AL), quinine sulphate, sulphadoxine-pyrimethamine (SP), and all other types of antimalarial drugs. Panel B contains summary statistics of transaction price by brand of the most commonly purchased active ingredient, artemether-lumefrantrine (AL). The conversion rate is approximately \$1=2583 UGX.

Table 4: Summary Statistics and Balancing: Analysis Sample

VARIABLES	All Visits (N=879) (1)	T1 Know Only Malaria (N=218) (2)	T2 Know Only AL (N=220) (3)	T3 Know Malaria & AL (N=211) (4)	Control No Information (N=230) (5)	Equal means test p-value: Cross-section (6)	Village FE (7)	Village & shopper FE (8)
Drug Shop	0.535	0.477	0.541	0.536	0.583	0.0879*	0.035**	0.0432**
Clinic	0.392	0.431	0.405	0.370	0.365	0.335	0.466	0.568
Pharmacy	0.073	0.092	0.055	0.095	0.052	0.081*	0.066*	0.042*
Language=Runyankole	0.514	0.505	0.518	0.512	0.522	0.978	0.235	0.235
Language=English	0.158	0.138	0.168	0.194	0.135	0.267	0.171	0.078
Language=Luganda	0.328	0.358	0.314	0.294	0.343	0.405	0.166	0.058
Patient = Uncle	0.498	0.450	0.500	0.526	0.517	0.475	0.413	0.351
Weekend Visit	0.422	0.394	0.409	0.460	0.426	0.455	0.460	0.525
Afternoon Visit	0.661	0.670	0.659	0.654	0.661	0.986	0.856	0.825
Had baby in shop	0.084	0.078	0.083	0.090	0.084	0.965	0.833	0.908
Female Vendor	0.794	0.780	0.759	0.820	0.817	0.252	0.506	0.442
Shop Had No Name	0.402	0.362	0.400	0.422	0.422	0.444	0.765	0.809
Visit Order	1.557	1.500	1.568	1.545	1.613	0.262	0.495	0.430
Female Shopper	0.593	0.541	0.582	0.573	0.530	0.673	0.696	—
Successful Bargaining	0.593	0.583	0.591	0.626	0.574	0.678	0.660	0.694

Notes: Above are sample averages for selected variables taken from the Shopper Transaction Survey, completed immediately after the shop visit. There are 6 observations that are missing values for one of the above variables. Establishment type is classified based upon the drug vendor census. Language is the reported language of purchase by the shopper; "English" includes a mix of language as well. "Weekend Purchase" is a binary variable indicating whether the visit took place on either a Saturday or a Sunday. "Afternoon Purchase" is a binary variable indicating whether the visit took place between 12pm and 5pm. "Had baby in shop" is a binary variable indicating whether there was a small child in the shop at the time of purchase. "Female Vendor" is a binary variable indicating whether the shopkeeper or pharmacist ""Visit Order" indicates the order of visit to a specific outlet. "Successful Bargaining" is a dummy variable indicating whether the shopper received any discount after negotiating. All scripts are the randomly assigned script for the visit. Column (6) contains the p-value from an F-test of equal means testing whether the means are not different across groups in the cross-section. Column (7) contains the p-value from an F-test of means, conditional on a village fixed effect, testing whether the means are not different across groups. Column (8) contains the p-values from an F-test of equal means, conditional on a village and shopper fixed effects. All F-tests cluster standard errors at the outlet level. $p < 0.01, ** p < 0.05, *p < 0.1$

Table 5: Effect of Information on Drug Purchase

Variables	No drug in stock	Denied Sale	Purchased Drug	Bought AL	Bought SP	Analysis Sample	Purchase Index
Panel A: Any Information	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Any Information	0.008	0.016	−0.015	−0.024	0.017	−0.024	−0.041
	(0.014)	(0.014)	(0.018)	(0.027)	(0.020)	(0.021)	(0.036)
Panel B: Type of Information	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T1:Know Only Malaria	−0.002	−0.005	0.014	−0.017	0.033	0.005	0.016
	(0.017)	(0.014)	(0.021)	(0.033)	(0.025)	(0.027)	(0.041)
T2:Know Only AL	0.017	0.014	−0.019	−0.022	0.015	−0.38	−0.058
	(0.018)	(0.016)	(0.022)	(0.033)	(0.025)	(0.026)	(0.043)
T3:Know Malaria & AL	0.009	0.036**	−0.039	−0.034	0.004	−0.039	−0.078*
	(0.018)	(0.018)	(0.024)	(0.031)	(0.022)	(0.027)	(0.047)
Constant	0.017	0.052**	0.932***	0.808***	0.003	0.826***	0.023
	(0.038)	(0.026)	(0.046)	(0.076)	0.042)	(0.067)	(0.083)
Pvalue Malaria = 0	0.814	0.042	0.081	0.557	0.339	0.238	0.098
Pvalue AL= 0	0.622	0.108	0.264	0.553	0.815	0.24	0.221
Observations	1016	1016	1016	1016	1016	1016	1016
R-squared	0.277	0.242	0.293	0.36	0.312	0.309	0.221
Number of clusters	495	495	495	495	495	495	495

Notes: Sample is all visits (N=1016) where the shopper interacted with a person. Above table contains coefficient estimates from a linear probability model of different purchases and outcomes from visits. The script and patient in all specifications is the randomly assigned script/patient. "P-value Malaria=0" is the p-value from an F-test that the scripts indicating knowledge of malaria are jointly zero."P-value AL=0" is the p-value from an F-test that the scripts indicating knowledge of first-line treatment are jointly zero. "AL" refers to artemether-lumefantrine and "SP" refers to sulphadoxine-pyrimethamine. "Drug Was Tested" means that the drug purchase was able to be tested using the handheld spectrometer. The purchase index is the average z-score of the variables stockout, denied sale, purchased drug, bought AL, bought quinine, and bought SP, where "no drug in stock" and "denied sale" are coded as the inverse z-score.All specifications include village and shopper fixed effects. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 6: Effect of Information on Drug Prices

Panel A: Any Information	Price Offered, Full Sample (1)	Price Offered, Analysis Sample (2)	Price Offered of Rec Option (3)	Ln(Price Offered) (4)	Price Index (5)
Any Information	−0.128	−0.183**	−0.269**	−0.053*	−0.081***
	(0.095)	(0.093)	(0.111)	(0.030)	(0.031)

Panel B: Type of Information	(1)	(2)	(3)	(4)	(5)
T1:Know Only Malaria	−0.166	−0.230**	−0.143	−0.051	−0.081**
	(0.116)	(0.116)	(0.139)	(0.034)	(0.039)
T2:Know Only AL	−0.076	−0.129	−0.284**	−0.043	−0.070**
	(0.111)	(0.107)	(0.124)	(0.039)	(0.034)
T3:Know Malaria & AL	−0.142	−0.192*	−0.375***	−0.066*	−0.090**
	(0.106)	(0.107)	(0.131)	(0.035)	(0.035)
Observations	933	879	869	879	879
R-squared	0.557	0.572	0.518	0.528	0.574
Number of Clusters	471	459	458	459	459
Pvalue Malaria= 0	0.311	0.110	0.013	0.137	0.032
Pvalue AL= 0	0.409	0.193	0.012	0.172	0.029
Mean of Dep.	3.512	3.585	3.785	1.180	0.009

Notes: Sample in the first columns is all visits at which a drug is purchased. Sample in columns 2-5 is all visits at which a purchase was made and the drug could be tested (N=879). All estimates contain village fixed effects. All prices are in US Dollars. In Panel A, "Any information" refers to whether the mystery shopper was assigned to either know the diagnosis (malaria) or know the drug they wanted (AL). The price index is the average z-score of the following variables: price offer, price paid, highest price offered, lowest price offered, price variation, average price offered, and whether or not bargaining was successful. The script and patient in all specifications is the randomly assigned script/patient. All specifications include village and shopper fixed effects. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 7: Effect of Information on Profits

	All Visits		Conditional on Purchase and Drug Testing	
	Profit, Offer Price	Profit, Price Paid	Profit, Offer Price	Profit, Price Paid
Panel A: Any Information	(1)	(2)	(3)	(4)
Any Information	$-0.223**$	$-0.211***$	$-0.192**$	$-0.194**$
	(0.086)	(0.078)	(0.091)	(0.086)
Panel B: Type of Information	(1)	(2)	(3)	(4)
T1:Know Only Malaria	$-0.217**$	$-0.205**$	$-0.264**$	$-0.253**$
	(0.105)	(0.096)	(0.117)	(0.111)
T2:Know Only AL	-0.179	$-0.171*$	-0.102	-0.104
	(0.109)	(0.097)	(0.101)	(0.090)
T3:Know Malaria & AL	$-0.269**$	$-0.254***$	$-0.210**$	$-0.223**$
	(0.109)	(0.096)	(0.105)	(0.095)
Constant	1.628***	1.284***	1.758***	1.421***
	(0.318)	(0.286)	(0.232)	(0.226)
Pvalue Malaria= 0	0.034	0.023	0.058	0.041
Pvalue AL= 0	0.039	0.023	0.138	0.062
R-squared	0.430	0.406	0.553	0.533
Observations	984	984	876	876
Number of clusters	492	492	459	459

Notes: Sample in columns 1 and 2 is all visits at which a profit margin could be calculated based (N=984). The sample in Columns 3 and 4 is all visits in which a drug was purchased and the drug was able to be tested. Profit margins are calculated by subtracting the parish average unit cost for that brand from the price paid or the offer price. Visits in which there was no sale are coded as zeros. Prices are in US dollars. Brands for which there was no recorded unit cost at the parish level were set to the average cost of that brand at the district level. The script in all specifications is the randomly assigned script. In Panel A, "Any information" refers to whether the mystery shopper was assigned to either know the diagnosis (malaria) or know the drug they wanted (AL). "P-value Malaria=0" is the p-value from an F-test that the scripts indicating knowledge of malaria are jointly zero."P-value AL=0" is the p-value from an F-test that the scripts indicating knowledge of first-line treatment are jointly zero. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 8: Effect of Information on Offerings and Additional Products

Panel A: Any Information	Number of Options Presented (1)	Additional Products (2)	Menu Index (3)
Any Information	$-0.092*$	$-0.133***$	$-0.440***$
	(0.056)	(0.037)	(0.038)

Panel B: Type of Information	(1)	(2)	(3)
T1:Know Only Malaria	0.015	$-0.090**$	-0.072
	(0.085)	(0.044)	(0.045)
T2:Know Only AL	$-0.129*$	$-0.130***$	$-0.550***$
	(0.066)	(0.046)	(0.046)
T3:Know Malaria & AL	$-0.159**$	$-0.177***$	$-0.686***$
	(0.062)	(0.045)	(0.044)
Constant	$1.748***$	$0.615***$	0.083
	(0.160)	(0.087)	(0.089)
Pvalue Malaria= 0	0.023	0.001	0.000
Pvalue AL= 0	0.031	0.000	0.000
Observations	879	879	879
R-squared	0.268	0.338	0.495
Number of clusters	459	459	459

Notes: Sample is all visits (N=879) where the shopper interacted with a person and a drug was purchased. In Panel A, "Any information" refers to whether the mystery shopper was assigned to either know the diagnosis (malaria) or know the drug they wanted (AL). Outcomes where the dependent variable is a dummy variable are estimated using a linear probability model. The menu index is the average normalized score for all outcome variables within the family of menu offerings: whether or not there was a recommendation made, the total number of drugs offered, and whether or not the shopper was offered additional products. The script and patient in all specifications is the randomly assigned script/patient. All specifications include village and shopper fixed effects. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 9: Drug Quality

	Correct dosage	Diverted Drug	Counterfeit	Substandard	Fraction Substandard	Quality Index
Panel A: Any Information	(1)	(2)	(3)	(4)	(5)	(6)
Any Information	0.041*	−0.039**	0.003	0.034***	0.025***	−0.596***
	(0.022)	(0.018)	(0.030)	(0.012)	(0.008)	(0.188)
Panel B: Type of Information	(1)	(2)	(3)	(4)	(5)	(6)
T1:Know Only Malaria	0.043*	−0.040**	−0.009	0.030*	0.014*	−0.352*
	(0.025)	(0.020)	(0.036)	(0.016)	(0.008)	(0.199)
T2:Know Only AL	0.043	−0.035	0.026	0.017	0.019*	−0.460**
	(0.026)	(0.023)	(0.038)	(0.013)	(0.010)	(0.231)
T3:Know Malaria & AL	0.037	−0.042**	(0.005)	0.054***	0.041***	−0.959***
	(0.025)	(0.020)	(0.035)	(0.019)	(0.012)	(0.292)
Constant	0.928***	0.124***	0.111*	−0.035	−0.050**	0.159**
	(0.037)	(0.044)	(0.057)	(0.033)	(0.025)	(0.076)
Pvalue Malaria= 0	0.184	0.069	0.966	0.009	0.002	0.003
Pvalue AL= 0	0.213	0.115	0.674	0.021	0.003	0.005
Observations	879	879	879	879	879	879
R-squared	0.268	0.471	0.217	0.208	0.248	0.239
Number of clusters	459	459	459	459	459	459
Mean of Dep Variable	0.909	0.100	0.174	0.013	0.001	−0.017

Notes: Sample includes all visits at which a drug was purchased and drug quality could be assessed (N=879). Counterfeit is a dummy variable for whether any tablet in the purchased sample did not pass the spectrometry test under repeated testing. Substandard refers to whether there was at least one tablet that could not be found to be matched to any other high quality tablets. The fraction of substandard tablets is the fraction of the dosage sold that were determined to be substandard. Diverted drug is an indicator for whether or not the purchased dosage had public sector markings. The drug quality index is the average z-score of the following variables (positively coded) correct dosage, (negatively coded) diverted drug, counterfeit, substandard, fraction of tablets substandard, and fraction of tablets counterfeit. Regressions include village fixed effects and controls for patient, visit order, and shopper. All scripts are the randomly assigned script. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 10: Service Quality

	Rational Use of Medicines			Customer Service			
	Express Doubts About Malaria	Advised Malaria Test	Ask Health Questions	Gave Enough Time	Explain All Options	Very Friendly	Service Quality Index
Panel A: Any Information	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Any Information	−0.044	−0.068*	−0.047*	−0.119***	−0.085***	−0.028	−0.126***
	(0.033)	(0.037)	(0.026)	(0.024)	(0.029)	(0.021)	(0.030)
Panel B: Type of Information	(1)	(2)	(3)	(4)	(5)	(6)	(7)
T1:Know Only Malaria	−0.057	−0.02	−0.018	−0.056**	−0.072*	−0.004	−0.069***
	(0.039)	(0.047)	(0.031)	(0.028)	(0.037)	(0.027)	(0.037)
T2:Know Only AL	0.009	−0.022	−0.026	−0.113***	−0.080**	−0.050*	−0.090**
	(0.043)	(0.046)	(0.033)	(0.031)	(0.037)	(0.026)	(0.039)
T3:Know Malaria & AL	−0.082**	−0.158***	−0.097***	−0.186***	−0.104***	−0.03	−0.217***
	(0.039)	(0.044)	(0.033)	(0.033)	(0.035)	(0.027)	(0.037)
Constant	0.227***	0.246***	0.447***	0.169***	0.335***	0.179**	−0.374***
	(0.079)	(0.086)	(0.082)	(0.063)	(0.086)	(0.078)	(0.071)
Observations	867	867	867	867	867	867	867
R-squared	0.333	0.321	0.638	0.659	0.57	0.434	0.566
Number of clusters	459	459	459	459	459	459	459
Pvalue Malaria=0	0.103	0.000	0.010	0.000	0.012	0.517	0.000
Pvalue AL=0	0.035	0.001	0.011	0.000	0.010	0.144	0.000
Mean of Dep	0.261	0.409	0.752	0.752	0.735	0.116	0.041

Notes: Sample includes all visits at which a drug was purchased and the purchased drug was able to be tested. Sample excludes observations with at least one missing value of a service quality variable. Service quality index is an index created from the z-scores of the following variables: whether the vendor gave the shopper enough time to ask questions, whether the shopper felt as if the vendor explained all of their options, whether the vendor advised the patient to take a malaria test, whether the vendor was rated as very friendly, unfriendly, whether the vendor expressed doubts about the patient's diagnosis. All scripts are the randomly assigned script. Regressions include village fixed effects and controls for patient, visit order, and shopper. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 11: Surveys from Real Customers

Panel A: Transaction Data	All Customers (N=372) (1)	Any Information (N=178) (2)	No Information (N=194) (3)	Difference (4)	With Village FE (5)
Bought AL	0.608	0.539	0.670	0.010***	0.318
Malaria Test	0.310	0.191	0.420	0.000***	0.000***
Bought Add Product	0.557	0.475	0.632	0.002***	0.062*
Product Price	2.53	2.19	2.84	0.000***	0.006***
Total Bill	3.05	2.34	3.70	0.000***	0.002***

Panel B: Demographic Data	(1)	(2)	(3)	(4)	(5)
Repeat Customer	0.778	0.698	0.853	0.000***	0.000***
Years of Education	9.423	8.927	9.881	0.020 **	0.027
Less Prim School	0.253	0.281	0.228	0.244	0.270
Less Sec School	0.704	0.730	0.679	0.277	0.318
Distance From Shop	23.3	26.0	20.8	0.108	0.613
Mosquito Net	0.823	0.818	0.828	0.804	0.432
Malaria Literacy	0.737	0.735	0.740	0.845	0.512
Have child in HH	0.755	0.747	0.763	0.726	0.745
Borrowed Money	0.150	0.154	0.146	0.832	0.963
Income	152.02	152.03	152.01	0.999	0.822
Female Respondent	0.505	0.497	0.513	0.763	0.460

Notes: Sample in above table is all respondents to the exit interview of customers at shops in the study who reported buying an antimalarial drug (N=372). Column (2) refers to the sub-sample of the entire group of antimalarial customers who reported with asking the vendor for a diagnosis or a product recommendation ("Any Information"). Column (3) refers to the sub-sample of the entire group of antimalarial customers who reported with asking the vendor for both a diagnosis and a product recommendation ("No Information"). Within columns 1-3 are averages of non-missing values for that subsample; Column 4 contains p-values of whether Column 2's average is equal to Column 3's average. Column 4 contains p-values of the same test, only inclusive of village fixed effects. There are 87 villages. All prices and income variables are expressed in 2013 US dollars; the exchange rate is $1US = 2593 UGX. Price paid is the transaction price of the primary item, and total bill is the total bill inclusive of any additional products purchased. Bought additional products is a dummy variable for whether or not the individual purchased additional products during the visit. Price paid is the total amount for the primary antimalarial drug. Total bill is the total amount, inclusive of additional products. Repeat customer is a dummy variable indicating whether or not the customer reported buying from the shop before this purchase. Years of education is a calculated measure based upon categorical responses to what level of education the respondent had completed. Prim School or Less is a dummy variable for whether or not the respondent had completed primary school; Sec school was whether or not the respondent had completed secondary schooling. Distance to shop is self-reported minutes spent walking to shop, and excludes those who said that they do not live within walking distance. Mosquito net is a dummy variable whether the respondent to the survey reported they slept under a mosquito net the previous night. Borrowed money is whether or not the respondent had borrowed money from family or friends to complete the purchase. Income refers to self-reported income the previous month, including income from the sale of crops. Malaria literacy score is an aggregate percentage correct of 6 questions on malaria transmission. Have a child in the household is a dummy variable for whether the respondent had a child under 5. Female refers to whether the respondent was female. Statistical significance is determined using robust standard errors, clustered at the outlet level.

Table 12: Exit Interview Reported Reasons for Choosing Store

	Customer Service			Other Store Characteristics		
VARIABLES	Customer Care	Knowledgeable Staff	Fast Service	Cheap Prices	Convenience	Product Selection
	(1)	(2)	(3)	(4)	(5)	(6)
Real Customer with Information	−0.236***	−0.110*	−0.180**	−0.089	−0.074	−0.068
	(0.067)	(0.059)	(0.071)	(0.062)	(0.063)	(0.051)
Bought Adult	−0.019	−0.064	0.03	0.083	−0.042	0.062
	(0.111)	(0.105)	(0.106)	(0.097)	(0.102)	(0.072)
Ln(Income)	0.04	−0.007	0.045	0.000	−0.067*	0.019
	(0.035)	(0.038)	(0.040)	(0.032)	(0.037)	(0.030)
Years of Education	−0.002	0.006	0.01	0.002	0.015	0.014*
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.008)
Constant	0.416**	0.430**	0.206	0.224	0.892***	−0.062
	(0.173)	(0.166)	(0.186)	(0.153)	(0.169)	(0.129)
Observations	322	322	322	322	322	322
R-squared	0.276	0.281	0.299	0.288	0.298	0.34

Notes: Results are taken from exit interviews with customers at study outlets purchasing anti-malarial drugs for an adult. Respondents are classified according to their responses on the exit interview: whether they asked for a diagnosis, and whether or not they asked the vendor for a recommendation. All regressions contain village fixed effects. Repeat customer is a dummy variable indicating whether or not the customer had previously shopped at that outlet. Price paid is the price of the primary item that was purchased, and total bill is the price paid for the entire transaction, including other side items. Prices are reported in US dollars. The conversion rate is approximately \$1 = 2593 UGX. Bargain over price refers to whether the respondent attempted to bargain for a lower price. Bought additional products refers to whether the customer bought other types of products in addition to the primary antimalarial drug. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 13: Hedonic Regressions

	—Price Paid—		—Ln(Price Paid)—	
	(1)	(2)	(3)	(4)
Service quality index	0.367**	0.320**	0.076**	0.051*
	(0.156)	(0.146)	(0.035)	(0.027)
Drug quality index	0.013	0.025	0.012	0.018
	(0.017)	(0.016)	(0.012)	(0.012)
Constant	2.689***	2.474***	0.966***	0.920***
	(0.224)	(0.273)	(0.066)	(0.052)
Brand Fixed Effects		X		X
Observations	867	867	867	867
R-squared	0.56	0.65	0.521	0.76

Notes: Sample is the analysis sample, all visits resulting in a drug purchase that could later be tested (N=879). Prices paid are in US dollars. The exchange rate at the time of data collection is approximately \$1USD = 2593 UGX. Service quality index is an average z-score of the following variables: whether the provider reported asking questions regarding health; whether the provider gave sufficient time to the shopper; whether the shopper felt like all of their options were explained to them; whether the vendor was reported as either friendly or unfriendly, whether the patient was advised to take a malaria test, and whether the vendor expressed doubts regarding the diagnosis of malaria. Unfriendly is coded negatively. The drug quality index is the average z-score of the following variables (positively coded) correct dosage, (negatively coded) diverted drug, counterfeit, substandard, fraction of tablets substandard, and fraction of tablets counterfeit. All regressions control for village fixed effects. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

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