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

Anne Fitzpatrick*
University of Michigan

May 30, 2015

Job Market Paper

Abstract

As in other markets with experts, healthcare markets are characterized by asymmetric information. Providers may use this information advantage to increase profits. I conduct an audit study to test whether improved customer information about healthcare purchases improves customer well-being through reducing prices and improving quality. I send pairs of covert shoppers to medical outlets in Uganda to purchase antimalarial drugs according to randomized scripts. The scripts experimentally vary information about the patient's diagnosis (malaria) and/or about appropriate treatment (artemether-lumefantrine). I test the purchased drugs using a spectrometer to determine whether they are substandard, an objective measure of quality. I find that shoppers who know either the diagnosis or recommended treatment pay approximately $0.18 (5 percent) less. I find that measures of quality observable at the time of purchase improve: informed customers are 4 percentage points more likely to receive the correct dosage. However, I find a corresponding decrease in actual drug quality, unobservable at the time of purchase. Shoppers who know either the diagnosis or the recommended treatment are 3.4 percentage points more likely to be sold a substandard drug. I interpret results through a framework in which providers trade off the short-run profits of selling a bad drug against the effects on their reputation if they were caught. I conclude that while shoppers with more information pay lower prices, providers may also lower quality in order to maximize profits. Thus, information asymmetries are difficult to correct and and information alone is unlikely to improve drug quality.

JEL: D83, I11, I15, L15, O12

*735 S. State St., Ann Arbor, MI, 48109. Email:fitza@umich.edu. I am grateful for financial support from the following sources: UM Department of Economics MITRE grant, National Science Foundation Dissertation Improvement Grant (#1260911), the UM Department of Afro-American and African Studies; the UM African Studies Center; the Rackham Graduate School International Research and Graduate Research Awards; the Center for Public Policy in Diverse Societies Research Grant; Center for International Business Education Research Grant; the Center for the Education of Women Research Grant. This paper does not necessarily reflect the views of the NSF or other donors. I am thankful to Kim Redic, Bob Brush, Thermo-Fisher Scientific Instruments, David Sherman, and Eli Eisman for providing technical assistance with the drug testing. I have benefited from comments from Rebecca Thornton, Jeff Smith, Steve Salant, Raj Arunachalam, Achyuta Adhvaryu, Susan Godlonton, Dusty Grundmeier, Varanya Chaubey, Ryoko Sato, Emily Beam, Desmond Toohey, Holly Painter, and seminar participants at the University of Michigan. Esther Atukunda and the entire research field staff provided essential support in implementing this project. This study received ethical approval from the UM-IRB (HUM00067957 and HUM00091197), the MUST-IRB (No. 18/09-12), and the UNCST (IS-93).

1 Introduction

Because they possess superior information on their products and services, healthcare providers have substantial power to influence the treatment choices of patients [Arrow, 1963]. Although patients expect healthcare providers to advise treatments to maximize patient well-being, providers may instead use this information advantage to increase profits. For example, providers may selectively increase prices, advise unnecessary services, or substitute lower quality products or services for unsuspecting customers due to conflicts-of-interest. This situation is possible because healthcare is an experience good- patients only realize the good's quality after it is consumed, and not at the point of purchase [Darby and Karni, 1973]. To correct the resulting asymmetric information and improve market efficiency, a commonly advocated policy recommendation is to educate and empower patients or customers. In this paper, I test a key assumption behind this policy approach. Does increased customer information improve customer well-being?

In the absence of effective regulation, asymmetric information may contribute to the widespread prevalence of low-quality healthcare in developing countries.[1] Existing evidence suggests that the quality of healthcare services is low, particularly among the poor and uneducated [Das and Hammer, 2014]. In addition, recent work has found that low quality drugs are also prevalent. According to a recent meta-analysis, approximately one-third of antimalarial medications 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 represent wasted consumer expenditures, may delay or interfere with individuals obtaining effective treatment, and also increase drug-resistance [Okeke et al., 1999].

This paper presents estimates of how providers adjust price and quality when customers have relatively more information about their purchases. Existing research has focused on comparing the prices paid and services received by experts compared to the general population (i.e., situations with symmetric information) or how public releases of information affect supplier behavior. For example, Johnson and Rehavi [2014] estimate how providers respond

[1] This echoes a common paraphrase of Gresham's Law: bad money drives out good.

[2] It should be noted that the imprecise terminology contributes to the apparent increase in counterfeit drug rates 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.

to an exogenous change in financial incentives by comparing differences in caesarean section rates when physician-patients give birth compared to when non-physician patients give birth.[3] Related literature in non-healthcare markets with "experts" finds similar differences between prices paid by experts and the general population.[4] For example, Levitt and Syverson [2008] show that 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 compared to regular customers. The provider response to publicly available information to consumers, such as healthcare "report cards", finds more mixed results. Kolstad [2013] finds that surgeons improve the quality of treatments given to patients due to intrinsic motivation to beat the competition. Using a very similar policy experiment, however, Dranove et al. [2003] show that surgeons selectively refuse to treat sicker patients to increase their "grade", thus negating any benefits to consumer welfare.

Empirically, there are two challenges in this literature. First, establishing a causal link between customer information and how providers respond is difficult. Customer information is not distributed randomly throughout the population. Customers who "take-up" information may be systematically different from those who do not, leading to a correlation of information and other characteristics of demand. While information may increase bargaining power, leading to a negative relationship between information and price, the reverse story is also possible. If providers believe that more informed customers also have higher incomes, then a standard price-discrimination argument would predict providers to charge higher prices to more informed customers. Previous experimental work in the taxi market has found that customers who know where their destination is, and who speak the local language pay lower prices. This effect is driven both by increasing the likelihood of being taken on a more direct route (i.e., a reduction in over-treatment), and decreasing the likelihood of being overcharged [Balafoutas et al., 2013]. However, the peculiarities of health markets may pose a greater chal-

[3]There is a related, large body of research on whether health providers adjust treatment recommendations in response to financial incentives. While still debated, these problems of "agency" have been found in various healthcare markets, including those related to chemotherapy drugs, cesarean sections, and prescription medicines [Currie et al., 2011, Yip, 1998, Jacobson et al., 2010]. There is also a substantial literature on whether improved health information changes behavior and ultimately demand for healthcare, which generally finds changes in behavior and beliefs but fewer changes in terms of product or service demand [Meredith et al., 2013, Madajewicz et al., 2007, Godlonton et al., 2014].

[4]In non-health markets, strategic behavior is typically referred to as 'provider agency,' while, in health markets, it is called "provider-induced demand" [Evans, 1974]. See McGuire [2000] or Chandra et al. [2011] for comprehensive reviews of the literature on health provider motivations.

lenge. It may be that everyday customers or patients simply cannot signal the same knowledge and experience level as experts. Second, quality is an important dimension of consumer well-being, yet one that is difficult to measure. In healthcare, for example, the treatment chosen by providers is typically based upon opinion regarding the best treatment for a specific patient. It is therefore difficult to identify unnecessary from essential treatment, and similarly low quality treatment from high quality treatment.

This study is designed to address each of these challenges. I conduct the first experimental evaluation to test how providers respond to two types of information that an ordinary customer might present at the time of purchase: information of what illness he has (diagnosis), and information regarding the appropriate treatment. Covert shoppers purchase antimalarial drugs according to randomly assigned scripts that vary whether the customer states the patient's diagnosis and/or asks for a specific treatment. Shoppers fill out a survey on the transaction and all purchases are tested to determine objective quality using a handheld spectrometer. I then compare conditional mean differences in price and quality outcomes between the randomly assigned scripts. The randomized design rules out confounding supply or demand characteristics that may determine equilibrium outcomes in practice. Moreover, implementing this study in the antimalarial drug market allows for a clear interpretation of the supplier response. In contrast to other areas of healthcare, the treatment recommendations for malaria are constant across all patients. Thus, there are no patient-specific differences in appropriate treatment choices, as opposed to a "gray" area of medicine. My design results in one type of drug purchased, and my measure of drug quality is objective.

I find that improved customer information does not necessarily translate into improved customer welfare. Customer information is effective at lowering prices, but may not improve quality. Customers who know the disease and know what treatment they want pay \$0.18 (5 percent) less than customers who ask a provider for a diagnosis or a recommendation, holding constant the type of drug purchased. This gap would have increased to \$0.27 if customers asking for a recommendation had bought the recommended product. However, I find that the effects of information on quality depend upon whether the quality is observable at the time of purchase. For example, customers with information regarding the product are 4 percentage points more likely to receive the correct dosage– a version of "quality" that is verifiable at the time of purchase. In contrast, I find that customers with more information about their purchases are 3.4 percentage points more likely to purchase a substandard medicine, a form of quality only known after the drug has been consumed. I find that drug quality is relatively high compared to previous studies: 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 substandard drugs are relatively rare, I find that nearly all of the substandard drug purchases are among customers with relatively more information. Provider effort, defined as whether the provider follows a "checklist" of medical protocol, also falls by approximately 8 percentile points among better-informed customers. While informed consumers may gain from lower prices, the net effect on consumer welfare from increased information is ambiguous due to decreases in quality.

I develop a conceptual framework of an experience good to demonstrate the interaction between consumer information, provider effort, prices, and quality. The experience good framework differs from the standard framework in that quality is only revealed after the purchase is completed; therefore, quality can only affect future purchase decisions. There are two types of customers, informed and uninformed, and type is common knowledge. For each group, firms trade off current benefits from selling a "bad" drug against the potential future profit losses from selling a bad drug. Customers who are sold a bad drug never return, but customers who are sold a good drug return with some exogenous probability. Firms exert costly effort solely to make the customer agree to buy the drug. Thus, effort and price are positively related. To predict the effect on drug quality, I consider where type does not let a customer distinguish good" from bad" drugs, as in a typical experience good setting. In this case, price and quality are not necessarily correlated. Instead, other demand characteristics of the consumer type dictate the optimal choice of quality. I then consider where type lets a customer distinguish "good" from "bad" drugs. If this assumption holds, then quality must improve. I find implications of this simple model are consistent with other data that I collect.

This paper measures the impact of increased customer information in an important market for global health with substantial problems of asymmetric information. Malaria is a widespread disease throughout sub-Saharan Africa with severe economic and health consequences.[5] Despite malaria's prevalence, misconceptions are common, and there is substantial

[5] 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].

evidence that the average customer lacks sufficient information with respect to both malaria diagnosis and treatment. The findings here suggest that information campaigns are complementary to widespread subsidies aimed at improving access to medicines, although average prices remain high for the population. However, as long as there is heterogeneity in take-up of information programs, providers may use information in order to charge by "type" and extract more surplus. The substantial decrease in both provider effort and drug quality rationalizes why information asymmetries persist, particularly for a common disease. Information may not be as valuable to learn or retain if it lowers prices, but also lowers the overall quality resulting from the transaction. Increased regulation may instead be needed to ensure that lower prices do not also result in lower quality. Finally, the results of this audit study suggest that while provider agency is useful at expanding access to care, particularly in rural areas, improved customer information unsurprisingly does not improve the targeting of antimalarial drugs to the truly sick. According to the rational use of medicines, antimalarial drugs should only be dispensed following a positive blood test, or at least diagnosis based upon clinical symptoms. However, only half of providers reported they sold or dispensed malaria tests. Conditional on testing, only half of covert shoppers were advised to have the patient take a malaria test. Finally, only advise a only 3 percent of shoppers purchasing for a fictitious patient report being denied a sale, when according to best practices all should have been denied.

This paper is organized as follows: In Section 2, I outline why the private sector for antimalarial drugs in Uganda is 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 strategy. In Section 7, I summarize my results and in Section 8, I conduct robustness checks and discuss mechanisms and policy implications. In Section 9, I conclude. Appendices are available on my website.[6]

2 Study Background

Healthcare markets in Uganda differ substantially from regulated markets in developed countries. In this section, I first outline anti-malarial treatment protocol and the problems of

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

low-quality medicines. I describe how this study contributes to the nascent literature on low quality drugs by testing a hypothesized solution: improve customer information. Next, I give background information on malaria and 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 Malaria and Treatment

Although malaria is a treatable disease, it is the second leading cause of death for children under the age of five worldwide and the most common illness in Uganda.[7] The average child has approximately two episodes per year, and the average adult has an episode approximately every other year.

In Uganda, the recommended first-line treatment for malaria is artemether-lumefantrine (AL). The clinical efficacy of AL for uncomplicated malaria ranges from 95 to 100 percent for both adults and children [Makanga and Krudsood, 2009].[8]AL is part of a larger class of medicines known as artemisinin-based combination therapies (ACTs) that combine multiple effective therapies so as to limit future drug resistance. 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]. Quinine, another commonly available treatment, is intended to be reserved for more serious ("complicated") cases of malaria , or used 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 [Uganda Bureau of Statistics, ICF International, 2012].

2.2 Low Quality Drugs

Low-quality drugs may harm individuals by delaying effective treatment or wasting money. They are also a public health concern, as they contribute to drug-resistant diseases [Okeke et al., 1999]. Although the precise impact on human health and welfare is unknown, low-

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

[8]AL is not recommended for those with the sickle-cell trait, but the fraction with this mutation is approximately 4 percent in the study area [?].

quality antimalarial drugs appear to be widespread. According to a meta-analysis, nearly one-third of antimalarials in sub-Saharan Africa are of low-quality [Nayyar et al., 2012].[9]

It is also unknown which interventions are the most cost-effective for improving drug quality. Recent studies have used larger sample sizes and randomized designs to determine that introducing a competitor with a high level of drug quality (such as an NGO, or a chain store) improves drug quality and also drives down prices [Bjorkman et al., 2012, Bennett and Yin, 2014]. Whether demand-side interventions, such as customer information, would be effective at improving drug quality has not yet been evaluated.

2.3 Demand for Anti-malarial Treatment

Although malaria is a common disease, average levels of customer information about appropriate treatment remain low as a result of two related factors: a reliance on symptomatic diagnosis and low levels of overall health literacy. These factors are not limited to Uganda, but generalize to other countries within sub-Saharan Africa.

There are four primary symptoms of malaria–headache, chills, fever, and nausea. However, the symptoms of malaria overlap with the symptoms of other bacterial or viral infections, thus making symptomatic diagnosis highly error-prone. In order to prevent drug-resistance from unnecessary utilization of first-line treatment, the official WHO guidelines state that symptomatic diagnosis should be confirmed with parasitological testing whenever possible: either blood microscopy or rapid diagnostic malaria test. Testing is not available at all outlets, however, and is relatively expensive compared to the costs of presumptive treatment. As a result, only 39-53 percent of adults seeking treatment for malaria at private sector facilities have tested positive according to a blood test [Littrell et al., 2011, Cohen et al., 2015]. Adhvaryu [2014] shows that repeated misdiagnosis introduces noise and makes learning of new medical treatments more difficult. This may lead to an approximately a 50 percent of those seeking treatment for malaria but testing negative purchasing antimalarial drug anyway Cohen et al. [2015].

Low health literacy is also a problem. Numerous studies have demonstrated low levels of customer information about malaria transmission, diagnosis, and treatment in a variety

[9] For a review of the existing literature, see Kelesidis et al. [2007] or our companion paper Atukunda and Fitzpatrick [2015]

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, some also mistakenly believe that 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].[10] However, knowledge of malaria transmission mechanisms may not be revealed to providers at the time of purchase. Instead, customers may only reveal information at the point of sale directly relevant to the transaction, such as knowledge of specific drug choices.[11] There are no studies to my knowledge demonstrating that information of diagnosis or appropriate treatment affect economic outcomes.

2.4 Supply of Antimalarial Treatment

Current health policy focuses on increasing access to antimalarial treatment through both public and private sector providers. In 2001, Uganda eliminated user fees and made antimalarial treatment available for free in the public sector. As a result, service quality fell as facilities became overburdened. There are long wait times, drug stock-outs, and reports of rude staff [Konde-Lule et al., 2012, Xu et al., 2006].[12] One cause of drug stock-outs is that drugs are taken from public facilities, where they are free, and sold illicitly in private facilities. In order to deter resale, public-sector drugs have specific markings on both the tablets and packs. In spite of this effort, in my data, 8 percent of purchases from private sector outlets appear to have been diverted from public providers.[13]

In response to problems of distribution through the public health sector, between 60-80 percent of those seeking care for malaria choose the private sector first [Konde-Lule et al., 2012, Littrell et al., 2011, Uganda Bureau of Statistics, Uganda Malaria Surveillance Project National Malaria Control Programme and Macro, 2010]. The private sector consists mostly

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

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

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

[13] 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. Here I abstract away from whether this is welfare enhancing or decreasing, and instead focus on its classification as an illegal activity.

of drug shops and medical clinics, with some pharmacies.[14] Although there are officially clear distinctions between drug shops and clinics, including regulatory and minimum education requirements for owners, in practice the difference may be indistinguishable to customers.[15] 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 licenses [Stanback et al., 2011].[16]

Private sector providers are important sources of healthcare in their communities, and therefore are important agents for increasing access to essential medicines. As a result, more than $500 million has been spent through the Private Sector Co-payment Mechanism, formerly known as the Affordable Medicines Facility-Malaria (AMF-m), to finance large-scale manufacturing subsidies in the private sector.[17] 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.[18] There are no price regulations on medicines in Uganda.

3 Study Design

Fieldwork took place from May-August 2013 and consisted of several rounds of data collection. First, the sample frame was constructed by doing a census of vendors within randomly selected areas. Second, two different covert shoppers visited each outlet and each purchased a drug. Third, additional survey data were collected from the drug dispenser at each outlet, and from 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.

[14] It is estimated that there are approximately 17,000 drug shops and clinics throughout the country, and 440 registered pharmacies [Uganda Bureau of Statistics, ICF International, 2012].

[15] 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.

[16] This figure is roughly in line with my calculation that only 21-38 percent of dispensers have the minimum level of required qualifications.

[17] This figure is likely a substantial underestimate of the costs of initiatives to improve first-line antimalarial usage. The budget for the AMF-m was $8 billion, of which approximately 20 percent goes to medicines in both the public and private sectors; the budget for the Private Sector Co-payment Mechanism is part of a larger grant portfolio of the Global Fund, but still contributes millions to global subsidies. In addition, NGOs and other large-scale foreign aid programs, such as the President's Malaria Initiative, also contribute money and resources.

[18] Although my sample of real customers is not representative, the average price is approximately 3.3 percent of median monthly income, $96.

3.1 Sample Selection

Data was collected from 45 randomly selected parishes within 5 districts.[19] Study team members then conducted a census and mapped all drug outlets–primarily drug shops, clinics, and pharmacies– within study parishes with a corresponding physical description of the outside of the premises. Vendors in all outlets found during the census were considered target respondents. The final sample size of outlets used in the primary analysis is 459. Appendix A describes the power calculations informing the design, and Appendix B describes how the analysis sample was created. Additional details are also in Atukunda and Fitzpatrick [2015].

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 received the same script twice. Randomization was stratified by parish.

Two different covert 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.[20] The shopper then described the four clinical symptoms of malaria (headache, fever, shivering, and body aches) displayed by the patient, either an uncle or a father, who was back at home.[21] 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".[22] Shoppers then either 1) asked for artemether-lumefantrine (AL), the WHO-recommended first-line treatment of malaria, or 2)

[19]Bushenyi, Busia, Mbarara, Rukungiri, and Kampala (the capital) were the study districts.

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

[21]The patient was also randomly assigned independently of the shopper scripts. The patient was an adult male in the household in order to remove the possibility of pregnancy, for which there are different guidelines for treatment. Shoppers did not pose as patients themselves so as 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 hypothesized to be a difference in price between patients. I control for this randomization in all specifications, and the coefficient on the dummy is statistically insignificant in nearly all specifications.

[22]If the vendor responded with 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, vendors responded with another illness in only two transactions.

asked for a drug recommendation.[23] 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

All shoppers were given \$3.86 (10,000 UGX) in small denominations of used-looking money to pay for all transactions.[24] All covert 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, during scripts in which shoppers asked for a recommendation it would no longer be clear whether the resulting purchase reflected shopper or provider behavior. I overcome this challenge by implementing a drug purchase protocol in the event that multiple products were presented to shoppers 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 is not available, buy quinine.
3. If a full dose of quinine is not available, then buy the next cheapest antimalarial available (typically SP).
4. If none of these is available, buy any other antimalarial.
5. If a full dose of any antimalarial is not available, do not buy anything.

Shoppers then purchased the drug and filled out a survey on details of the transaction. Details include if another drug was recommended, the price of the recommendation, and other products. The total number of antimalarial options and details on up to three were recorded, as well as provider behavior and other observations. Supervisors monitored shoppers 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

[23] In the vernacular, AL is called "coartem". To avoid confusion with the originator brand Coartem®, by Novartis, I use the "AL" throughout the paper, although it is not the word used during the transaction.

[24] 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 charged 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.

visited the correct shop. For example, supervisors followed or led shoppers to shops in dense areas or areas in which shops might be difficult to find without attracting extra attention.

3.2.2 Bargaining Protocol

In this market, only 2.2 percent of prices are posted. Therefore, covert shoppers were also given directions on bargaining. They were provided with specific answers to common questions and told 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, because they were concerned 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 present the provider's offer price (i.e., the first price stated by the provider) as an outcome variable, and also in the calculation of per-transaction profits, in addition to the transaction price paid. In practice, results are slightly stronger when the price paid is used.

Covert shoppers were not allowed to retain the balance of their purchases. In this context keeping the balance is not incentive-compatible as it might induce them to manipulate or misreport prices or dosages.[25] It is not expected that this aspect of the protocol introduced 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, and they were not allowed to share price information between visits. Thus, they believed that any price differences between shoppers would be noticeable and would be suspicious. If shoppers did manipulate the reported price, it would need to be done in a manner correlated with the randomly assigned script to introduce

[25]First, shoppers could buy a half dose, report buying a full dose, and pocket the difference. There was no incentive in the current design to buy less than a full dosage, but this occurred in 8 percent of transactions. Second, shoppers could buy a cheaper drug, such as SP, and keep the balance, while reporting that AL was out of stock. Third, if shoppers believed that supervisors might reduce the budget later when shopping less expensive areas, they might inflate their prices at the beginning to ensure they would continue to keep a portion later. Fourth, in a real life purchase of a relatively expensive product– such as an antimalarial drug– the individual would be expected to return the balance. Over the entire course of employment, the excess balance would have been the equivalent of a huge windfall, also signaling that the project had no budget constraint. It is unclear how the shoppers (as employees) would have responded to that signal.

bias. This is unlikely, because neither shoppers nor supervisors were told the study expected to find price or quality differences between different scripts.[26]

3.3 Covert 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. Of the remaining shops, 2.27 percent received 1 visit; 6.19 percent received 3 visits; and 0.62 percent received 4 visits. The number of shops visited differs from the target of two per shop, because 1) visits in which 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 the latter instance, 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).

3.4 Drug Inspection and Quality Testing

At the conclusion of the fieldwork, all purchased drugs were inspected by research assistants. The recorded drug characteristics include brand, expiration date, number of tablets, and whether the drug had public sector markings. Drugs were then shipped to a laboratory at the University of Michigan for testing with a handheld Raman spectrometer, the TruScan™ RM.[27] Testing consists of comparing a purchased tablet with a separate, high-quality authentic tablet of the same brand. As part of testing I collected high-quality tablets from manufacturers and wholesalers in Uganda, and built a "spectral library" for the study.[28] Each purchased tablet was tested at least once. Appendix E details the testing protocol, with additional information

[26]Study team members were told that the purpose of the two visits was to collect more drugs for testing.

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

[28]The handheld spectrometer compares Raman spectra, or signatures, of two molecules. The spectrometer detects changes in the wavelength of light that occur 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.

on storage and handling.

3.4.1 Analysis Sample

Valid testing requires obtaining authentic, high-quality tablets, ideally from the brand manufacturer. I was able to obtain an authentic comparison tablet for 94 percent of samples (N=879). Where a high quality authentic sample could not be found, it was 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 the 879 drug purchases that could be reliably tested. I document when results differ between the full sample of purchases and the analysis sample.

3.4.2 Counterfeit vs. Substandard

In order to do analysis at the transaction level, I define "counterfeit" as a purchased dosage ("sample") for which at least one tablet failed the spectrometry analysis. Because many brands are chemically similar, in practice a tablet that failed the comparison against its own high quality authentic tablet could potentially match against another brand within the library. I define "substandard" as a purchased drug dosage that had at least one failing tablet that did not match any high-quality authentic in the library. Figure 5 presents a scan distinguishing between counterfeit and substandard. 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 with the same active ingredient.[29]

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

[29] Recent work by Bate et al. [2012] also differentiates between counterfeit and substandard medicines, although the authors use chemical assays. 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], who use a different testing methodology. However, my definitions reflect the current definition of counterfeit and substandard according to the WHO and Newton et al. [2009].

asymmetries and show that providers have market power to adjust prices.

4.1 Drug Prices: Mean and Variance

During shopping, 933 drugs were successfully purchased in 1016 visits to outlets. Figure 3 graphically demonstrates that there is substantial price dispersion among antimalarial drugs within a village, the variation that I use in the empirical analysis. Table 2 shows average drug prices by type of active ingredient among purchased drugs. Overall, AL (the first-line treatment) is the second most expensive drug type at $3.19, following other first-line treatments. Even though some brands of AL are heavily subsidized at the producer level, the medication is still expensive for consumers. It is is also the most commonly purchased drug in the sample. My results indicate a common availability throughout the selected study sites in Uganda, in contrast to previous evidence.[30]

Mean price differences mask the substantial variation in prices, even for the same type of drug. Panel B of Table 2 shows the average differences in prices by AL brand, for each of the 7 brands purchased during covert shopping. Most of the variance in price is across brand. Within the sample of AL used in the analysis, only 6 percent of variation was within brand. The average price of AL ranges from $2.85 to $3.86. The distribution of prices is graphed in Figure 4. Observed prices paid for a full dosage in the sample range from $0.19 to $25.07, and the coefficient of variation (CV) is 0.501.[31] 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. [2014] 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.

[30]O'Connell et al. [2011] conducted research in 2009 that found that only 13 percent of Ugandan private sector outlets had any antimalarial in stock at all, and, conditional on having any antimalarial in stock, only 20 percent had first-line AL treatment available. The large change is most likely due to increased policy focus on providing access to ACTs, as through the subsidy programs.

[31]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 the price of an appendectomy is 0.30, then the ratio of high/low will be roughly 3." (p.24).

4.1.1 Drug Testing Results

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 ("counterfeit"). 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 ("substandard"). Results from a chemical assay that will conclusively determine medical efficacy are not yet finished. In Atukunda and Fitzpatrick [2015], we discuss these averages in detail, present descriptive correlates, and compare our results to the previous literature.

4.2 Surveys of Real Customers

Surveys were conducted with a convenience sample of 867 real customers from 350 shops; 372 customers purchased an antimalarial drug. Although enumerators tried to interview three customers purchasing antimalarial drugs from every shop in the study, in practice this was not achieved. Reasons for imbalance include a high refusal rate (37 percent) and other logistical constraints.[32] For example, in some sample areas it was common for children to be sent to the outlet to buy medicine. Our protocol required that interviewed customers be over 18.[33] As a result, there is an imbalance in the number of interviews per outlet. Appendix Tables E1 and E2 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 reported on the vendor survey. In particular, there is no correlation between prices and quality and whether or not real customers were interviewed at the store.

Results from surveys of real customers suggest that the experimental protocol was consistent with true customer behavior. On the survey, approximately half of customers buying antimalarial drugs (52.3 percent) reported asking for both a diagnosis and a product recommendation, and 23 percent reported asking for neither a diagnosis nor a recommendation. Between 12-13 percent asked for either a diagnosis or a recommendation, but not both. Therefore, each study arm is observed among real customers. Similarly, 48 percent of antimalarial

[32] 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 non-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.

[33] A precise figure of how common children shoppers are is unavailable.

customers report successfully bargaining over the price of the drug, and 53 percent of antimalarial customers were buying for another adult within the household. Thus, covert shopper behavior is consistent with real shopper behavior.

4.3 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 between price or quality and survey completion. Correlates of survey completion are in Appendix Table E3.

Table 3 contains selected summary statistics of vendor characteristics. The average respondent is 30 years old and 23 percent are male. Only 8.9 percent of respondents live in the same parish that they were born in; this rate is low because 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.[34] The average vendor had been in that line of work for 6.2 years. Eighty-four percent of respondents correctly identified the first-line treatment for malaria (AL). Although the provider's level of information may not be perfect, it is likely higher than the average customer level of education. On a standard test of malaria transmission, providers score an 81 percent compared to 72 percent among customers.

Panel B contains relevant characteristics of the study outlets and their customers. Vendors report that their stores receive on average 22 customers per day, on average, of which approximately six 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 can test for malaria at their outlet; conditional on selling a test, the price was $1.09. Nearly half indicated that their outlets have beds to consult or treat patients, although only 14 percent report ever charging a consultation fee for treatment.

Outlets are small and somewhat profitable. On average, they have 2.4 employees, and

[34]These requirements vary based upon the establishment type, and (for clinics) how long the individual has had his or her degree [, 2013].

regulation is reported to be relatively high in the study area. Seventy-two 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 $436, the median value of monthly profits is $77.13, with nearly 9 percent of outlets reporting negative profits for the previous month.[35] The collected data also suggests that vendors have market power. On average, there are 10 outlets (including the respondent's outlet) in their market, where the market is defined as the village. The median value is five 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 [Commission, Federal Trade and US Department of Justice, US Department of, 2010]. Thus, consumers do have some degree of choice; only 6 percent are monopolists.

4.4 Calculation of Profit Measure

The vendor survey contained a module on the drug inventory at the establishment: 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," a relevant variable for providers to consider in dispensing drugs.

There are an average of 5.3 antimalarial drugs listed on the inventory section of the data, and on average 4.4 drugs listed are currently in stock; 1.83 of the drugs in stock are AL. Ninety-six percent of respondents report typically stocking AL at their outlet, and 90 percent of respondents report having AL in stock at the time of the drug vendor survey. Despite this extensive range of data, only 423 drugs purchased during covert 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 was not reported. There are several explanations. 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

[35] 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."

was confidential. Third, due to the observed average differences in prices and costs by brand, I only consider exact matches by brand. Finally, although they survey 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:

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

where profit varies at the transaction level t.[36] To 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 B4, I present additional support for the validity of this measure of per-transaction profits.[37] 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

In this section I present a simple framework of an experience good to motivate the empirical analysis. An experience good is a good where the quality cannot be assessed at the time of purchase, but rather after the purchase is complete.[38] I focus on the provider's decision to sell "bad" drugs or "good" drugs, an attribute of the good that is unobservable to customers

[36]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.

[37]I use prices from the covert 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.

[38]A similar, alternative framework would be a credence good, for which the quality of the good cannot be assessed even after the time of purchase.

at the time of purchase. A primary assumption is that quality does not enter the customer's utility in this period, because drug quality is only revealed after the transaction is completed. I contrast the results with the situation where quality can be assessed at the time of purchase.

5.1 Model Assumptions

Consider a market with two agents: a provider, and a customer. Providers only sell drugs, and can choose to sell either a good quality drug ($q = G$), or a bad quality drug ($q = B$). There are different costs to the provider for the drug depending on its quality, $c^G > c^B$, and providers have market power to set the price. Providers supply costly effort, $e(s)$.[39] Providers therefore choose prices, effort, and drug quality in order to maximize their payoff.

All customers are shopping on behalf of people sick with the same disease, and each demands one unit of a good. All customers have two choices: either to buy the drug, or to refuse the drug and shop elsewhere. There are two types of customers, informed or uninformed. I index customer type by $i \in \{I, U\}$. The customer's type is known.[40] In this context, "information" may refer to information regarding outside options or the whether the drug will cure their disease. Customers value service and provider input, s_i. The extent to which they value s_i is given by the parameter, θ.[41]

A crucial assumption is that *neither* type of customer can determine drug quality at the time of purchase, but both types can determine drug quality after the transaction is complete based on its efficacy. As a result, in order for the provider to have any incentive to ever sell a *good drug* there must be some sort of penalty to deceiving customers. I therefore incorporate payoff from future sales, where the lost future sales can be thought of as a "reputation cost" to selling low-quality drugs.[42] If any customer buys a bad drug, then they do not return to the provider. If a customer buys a good drug, then they return to the provider in the future with probability α, which may differ by type. They may not get sick again, or they may simply shop elsewhere next time. Therefore, the drug quality does not affect the current customer's

[39]The $e(s)$ function has the properties $e'(s) > 0, e''(s) > 0$.

[40]Thus, providers can charge customers according to their type.

[41]A simple extension of the model could be that customers with less information place a higher valuation on the provider's opinion: $\theta_I < \theta_U$. All results go through under this setup.

[42]This intuition is based upon the previous literature on credence goods, and is a standard feature of both models and empirical studies. See Hubbard [2002], Dranove [1988], or Schneider [2007], among others. In our data, 93 percent of vendors thought that the customer would stop shopping at their store if they were caught selling a bad drug [Atukunda and Fitzpatrick, 2015].

utility, but does affect the provider's future payoff.[43]

5.2 The Provider's Objective Function

The provider's problem can be written as follows:

$$\begin{aligned} \max_{p_i, s_i, q \in \{G,B\}} \quad & p_i - e(s_i) - c^q + \alpha_i^q \Pi_i(p_i) \\ \text{subject to} \quad & \theta s_i - p_i \geq 0 \end{aligned} \tag{3}$$

where p is the price charged, θ is the marginal valuation of service quality, s is service quality, α is the likelihood of returning to the same provider if the drug is of good quality, and Π is the future profits from that customer.[44] Customers of either type who are sold a bad drug never return; $\alpha^b = 0$.[45] I normalize the utility from the outside option to be 0 for both types.[46]

Note that the price does not signal drug quality. If price did signal quality, then drug quality would be at least partially observable at the time of purchase. Rational customers would see price differences and (correctly) infer the drug's true quality. Thus, the drug would not be an experience good. Similarly, drug quality cannot be part of the consumer's buying decision.

5.3 Solution

I first derive the relationship between price and service. Customer type is observable, so providers find the optimal price and effort choice separately by type. The provider charges a

[43]To keep the model as simple as possible, I assume no discounting of the future. In addition, I do not assume that there is a correlation between information and knowing the true drug quality. There is no empirical evidence that more informed customers are also those more likely to actually have malaria, and given widespread over-utilization, it is difficult to sign the correlation. In reality, the drug's true quality is possibly only revealed with some endogenous likelihood.

[44]To keep the equation as simple as possible, I have made Π solely a function of price. If Π were also a function of $e(s)$ then I would need an additional assumption for the following logic to hold. In particular, I would assume that the marginal increase in profits from an increase in price is greater than the marginal disutility on "profits" from providing better service. Formally, $\frac{\partial \Pi}{\partial p_i} \frac{\partial p_i}{\partial s_i} > \frac{\partial \Pi}{\partial e(s_i)} e'(s_i)$.

[45]To make the results hold, $\alpha^b > 0$, but $\alpha^g > alpha^b$. Equation (5) becomes slightly messier with no additional intuition.

[46]We could also write the outside option as $\bar{u_i}$, where $\bar{u_U} < \bar{u_I}$. In other words, all else equal, more informed customers are more willing to walk away from the sale. Because that assumption is stronger and unnecessary, I omit it. However, there is a nice intuition between outside options and repeated visits to the same provider. If in every period customers with increased outside options are more likely to visit other outlets, then rational providers must assume that customers with more knowledge are less likely to visit their store in particular (holding constant the total number of visits).

price and provides a service quality such that the customer is just indifferent between purchasing the drug there and seeking the drug elsewhere. Substituting the constraint $\theta s_i = p_i$ into the objective function and choosing the optimal s_i, we find the implicit function that defines s_i:

$$\theta(1 + \alpha_i \Pi(\theta s_i)) = e'(s_i) \tag{4}$$

This equation highlights that the optimal choice of service quality is increasing in α. Thus, customers with a higher likelihood of returning are given higher service quality.

Next, I consider the provider's choice of drug quality. Providers know drug quality. The provider compares the total profits from selling a good drug with the total profits from selling a bad drug. Let the revenue from the current sale be A. A provider will offer the good drug if, and only if

$$\begin{aligned} A + \alpha_i \Pi_i - c^G &\geq A - c^B \\ \alpha_i \Pi_i &\geq c^G - c^B \end{aligned} \tag{5}$$

Thus, so long as the expected future payoff from selling a good drug exceeds the one-period gain in profits from selling a bad drug, the provider will choose to sell a good drug. So which customer type is more likely to be sold a bad drug? Whichever group has the lower future profits– in this model, not visiting the provider again is the '"penalty". Therefore, if $\alpha_I \Pi_I \geq \alpha_U \Pi_U$, then informed types are more likely to receive a bad drug; otherwise, uninformed types are more likely to receive a bad drug. While theoretically ambiguous, empirically both the likelihood of returning and profits work in the same direction in that equation: customers with more information are more likely to receive a bad drug. My results show that providers make higher profits off of customers with less information, customers with less information are 16 percentage points more likely to visit the same vendor again.[47] This is somewhat intuitive: a rational provider would not want to risk losing a loyal customer from whom they make high profits.

[47]The negative correlation between information and treatment-seeking is also found empirically in Ingham and Miller [1983] and Das and Hammer (2013).

5.4 Alternative model: Quality is revealed at the time of purchase

What if quality were observable at the time of purchase, for the I type? This assumption corresponds to the standard lemons model with symmetric information, where the good in question is not an experience good [Akerlof, 1970]. Assuming type I customers do not agree to purchase drugs of low quality, then providers only offer them high quality drugs. Therefore, high quality drugs are always sold to type I, implying that type U must then be weakly more likely to buy a low quality drug. The equilibrium price, however, is still derived from equation 4, and is still based upon the effort cost and the likelihood of future visits from that customer. As long as type U still has a higher likelihood of future visits, then the price will still be higher among type U, and service quality will also be higher.

6 Empirical Strategy

My empirical strategy is to compare mean differences in price, options, and service quality between shoppers who recite randomly assigned scripts. I first test an implication of the identification assumption by showing that treatment groups display similar averages of observable characteristics. I evaluate whether customer information affects the provider's choice of price, quality, and service quality. 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 I handle standard errors and potential concerns of multiple outcomes hypothesis testing. The main estimating equation is:

$$Y_{st} = \alpha_0 + \alpha_1 AnyInformation_{st} + \gamma_v + \delta' X + \epsilon_{st} \tag{6}$$

where *Any Information* corresponds to whether the shopper stated that the condition was malaria, asked for a specific drug ("AL"), or both. Y is the outcome: measures of price, drug quality, service quality, and other relevant outcomes for transaction t in shop s located within village v. Because there are a 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_v, a village fixed effect.[48] I include a vector of covariates, X, consisting of shopper, visit order, and patient fixed effects to absorb residual variation and address potential concerns of omitted variables. I cluster standard errors at the shop level to account for any correlation of the error terms within shops with respect to outcome variables. There are 459 clusters in the analysis sample. In Appendix Tables E4-E9, I present the estimates with the multiple-outcomes adjusted p-values following Anderson [2008].

To test whether providers respond differentially to customers who present information of either diagnosis or their preferred drug treatment, I use the following specification:

$$\begin{aligned} Y_{st} = \beta_0 + \beta_1 KnowOnlyMalaria_{st} + \beta_2 KnowOnlyDrug_{st} + \\ \beta_3 KnowMalaria\&Drug_{st} + \gamma_v + \delta' X + \epsilon_{st} \end{aligned} \tag{7}$$

where *KnowOnlyMalaria* is a dummy variable indicating whether or not the shopper was randomly assigned to the treatment group "Know *Malaria*, Ask for Drug Recommendation". Similarly, *KnowOnlyDrug* is a dummy variable indicating random assignment to the "Ask for Diagnosis, Know *Drug*" group, and *KnowMalaria&Drug* is a dummy variable indicating random assignment to the "Know *Malaria*, Know *Drug*" treatment group. Each coefficient measures the average difference in outcome Y between the individual script "treatment" script and the "control" script, wherein the customer has no information about their purchase ("Ask for Diagnosis, Ask for Drug Recommendation"). Therefore, β_1 identifies the provider's response to a shopper with information of the diagnosis (malaria) only; β_2 identifies the provider's response to a shopper who only has information of the first-line drug treatment (AL); and β_3 identifies the provider's response to a shopper with information about both the diagnosis and the first-line drug treatment, compared to having information of neither.

Note that the dummy variables refer to the script randomly assigned, which may not always be the script the covert shopper actually used. In the analysis sample, three percent of

[48] In order to ease exposition, keep a consistent specification throughout the paper, and to maximize statistical power, I present results from a village fixed effect. A vendor fixed effect would remove the variation from outlets at which only one visit was conducted, and also outlets where two "Any Information" scripts were recited. Empirically, the difference in outcomes between Any Information and No Information is the largest.

scripts used for purchase differ from the assigned script. 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.

Assumption 1: *Random assignment was effective at creating four groups that are comparable on average characteristics.*

In order for estimated coefficients of interest to be unbiased, two identifying assumptions need to hold. First, 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, and are taken from the covert shopper data. Table 4 presents evidence that there are no systematic differences between scripts in the analysis sample. Appendix Table E10 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. The predominant local languages Runyankole and Luganda were used in approximately one-half and one-third of transactions, respectively. 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 dispensers are female, and 8 percent of shopkeepers have a baby or small child with them in the shop. In total, 42 percent of shops did not have a name. Female covert shoppers conducted 59 percent of visits, and bargaining resulted in a successful price reduction in 59 percent of transactions.

Columns 6-8 of Table 4 provide 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 statistically 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 effect (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.[49]

Assumption 2: *Providers react to information, not the experiment.*

Second, the shopkeeper must perceive all shoppers as identical on average except with respect to the randomly assigned script. Available evidence does not suggest this is a substantial source of bias. First, shoppers were extensively trained, and the protocol was reviewed every morning.[50] 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 vendor survey respondents reported that a covert shopper had ever visited them, and only 3 percent reported a covert-shopping visit during the time of our study. Moreover, as a robustness I test whether results differ by measures of competition in the village, or the number of customers that the outlet reported, and results do not differ (not shown).

6.2 Selection bias on purchases

One concern with the analyses of prices and quality is that I do not observe transaction prices from visits in which no drug was purchased. Therefore, if the likelihood of purchase is correlated with the randomly assigned script then there may be an issue of a selection bias for specifications conditional on purchase. I account for this potential problem by showing that whether the transaction is part of the analysis sample is uncorrelated with the randomly assigned script, alleviating concerns of internal validity. However, there may still be concerns of external validity. Second, I sign the selection bias term as negative. Third, I construct Lee

[49]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.

[50]Details of training are in Appendix F.

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 Table E11.

Overall, 96 percent of attempts to purchase a drug resulted in the shopper interacting with a shopkeeper. Unsuccessful visits occurred typically because the shop was temporarily closed (N=60). Of successful visits, 92 percent resulted in a purchase. In 3.3 percent of visits 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 of antimalarials. Results in Panel A of Table 5 show that presenting information does not change the likelihood of reporting that a drug is out of stock, being denied a sale, or making a purchase. Information also does not affect the likelihood of purchasing AL or SP, the most common classes of drugs purchased.

Although there is no correlation between having drugs in stock and the randomly assigned script, there are slight differences in being denied a sale across the treatment groups. Shoppers indicating the information of both malaria and appropriate treatment are 3.6 percentage points more likely to be denied a sale than those reciting the no-information control script. Although the likelihood of buying a particular type of drug is uncorrelated with the randomly assigned script, customers who knew both the diagnosis and the appropriate treatment score 0.08 standard deviations lower on the purchase index, significant at the 10 percent level.[51] Appendix Table E13 shows that whether clinics and outlets charge consultation fees is the most significant predictor of whether shoppers successfully made a purchase. Consultation fees are approximately double the cost of treatment (which the customer still pays), 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, these patterns suggest a negative selection bias term.

7 Results on the Provider Response to Customer Information

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

[51] Results are similar in the analysis sample. Although there is no difference for the purchase index across scripts, shoppers knowing only the diagnosis are 4.4 percentage points more likely to buy SP. See Appendix Table E12 for additional details.

7.1 Prices

Increased customer information decreases the price offered to shoppers for the same drug. Panel A of Table 6 presents estimates of the effect of any information on the price offered. In column 1, I show that in the analysis sample, providers charge customers showing any information approximately 5 percent less, \$0.18, than shoppers not showing any information. This effect is approximately the same for the offer price and the final transaction price. The data collected can be used to assess what would have happened if instead the shopper had bought the recommended option. Column (2) shows that if the shoppers asking for a recommendation 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. 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.[52]

Panel B shows that, in the analysis sample, the provider response does not differ by the type of customer information that is presented; shoppers who only state the patient's diagnosis are charged \$0.23 less, and shoppers who state 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 who know 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 lower, 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 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.

[52] In the full sample of all purchased drugs, customers with any information are charged \$0.13 less, although this value is not significantly different from zero (p-value = 0.177). Results similarly show suggestive evidence but no statistically significant effects for prices using either a level or a log specification due to a high amount of variation in the dependent variable. However, the effect of information on the price paid is significant when controlling for the type of drug purchased, which absorbs additional residual variance. See Appendix Table E14. In addition, dropping either the other high-quality antimalarials or the quinine drug types reduces variation sufficiently to obtain statistical significance. For example, other high-quality antimalarials are priced approximately \$2.18 more per dose than AL.

The calculation of Lee Bounds in Appendix Table E13 also 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. However, the construction of family-wise error rates, to control for multiple hypothesis testing, leads to some caution in interpretation. According to that procedure, the effects on price could be due to Type I error. The p-value on the offer price after accounting for the large number of outcomes, for example, is 0.158.

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.[53] Columns 1 and 3 calculate profits using the offer price; Columns 2 and 4 calculate 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 when a shopper shows information of diagnosis (malaria), provider profits fall by \$0.22, and showing both types of information lowers profits by \$0.27. sUsing 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. The difference in profits between treatment groups in the sample of purchases are similar in magnitude to the difference in price between treatment groups, and suggest that the lower profits are actually driven by reductions in price (as opposed to costs). This interpretation is supported by the fact that average costs by brand at the parish level do not differ by script (not shown). Results are robust to procedures that account for multiple outcomes testing.

7.3 Add-Ons

In addition to selling antimalarial drugs, outlets also commonly sell other products for the treatment of malaria symptoms: fever reducers, headache medicine, vitamins, and even an-

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

tibiotics. Results of Table 8 indicate that providers also potentially lose profits to 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 be offered additional products to relieve the symptoms of malaria. Overall, providers substantially decrease the menu of options presented by 0.44 standard deviations of the z-score index. Results are robust to procedures that account for multiple outcomes testing.

Panel B shows that the provider response becomes stronger as shoppers present more information. Shoppers who ask for a specific treatment are offered between 0.13-0.16 fewer antimalarial drug options. Shoppers who know the patient has 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 information 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, providers may also lose profits on shoppers showing more information by not offering them additional products and services.[54]

7.4 Drug Quality

In Table 9, I examine whether vendors adjust drug quality in response to customers with different levels of information. I find that increased customer information increases observable quality, but decreases actual 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 pack has public sector markings ("diverted").[55] These estimates correspond to testing the predictions generated in Section 5.4, if quality were observable at the time of purchase. For example, customers knowing what drug they want may also be more likely to know how many tablets are in a complete dosage. In the context of these 'observable" measures of quality, drug

[54]Note that providers could assume that customers with information do not want additional products. However, not offering additional products to certain groups would likely result in lower profits for that group.

[55]I classify a decrease in drugs with public sector markings as a quality improvement because data from the pilot indicate that these markings are widely known and it is illegal to sell these in the private sector. Moreover, anecdotal evidence suggests that Ugandans view selling these drugs as a form of corruption or deception (since they are intended to be free). In Atukunda and Fitzpatrick [2015], we show that actually these drugs are more likely to be substandard, even though public sector medicines must pass quality tests to enter the country.

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 public sector markings. The coefficients do not differ substantially in magnitude by the type of information presented for either dependent variable.

Columns 3 -5 present estimates of whether the drug is counterfeit or substandard, a measure of drug quality not known at the time of purchase. Although the level and kind of customer information has no effect on the likelihood of purchasing a counterfeit drug, there is a relatively large and significant difference in the likelihood of buying a substandard drug. Shoppers who state either the diagnosis or the treatment they want are 3.4 percentage points more likely to buy a substandard drug. Shoppers who state the patient's diagnosis are 3 percentage points more likely to buy a substandard drug, and shoppers stating both diagnosis and the first-line treatment are 5.4 percentage points more likely to buy a substandard drug. Although these results are based off a small proportion of the sample, they are robust to using the fraction of dosage that is substandard, the z-score index of drug quality, and multiple outcomes hypotheses corrections. This result is also not driven by switching across different drug classes with different substandard rates. The calculation of Lee Bounds in Appendix Table E11 shows that all of these estimates 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 the drug was substandard is small and insignificant, it is still positive.[56]

Interpreting these results as strategic behavior relies on the assumption that vendors know whether drugs are of high or low quality but that customers do not. Available evidence supports this assumption. First, 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. Only 6 percent of outlets sell low-quality drugs. At a minimum only 6 percent of the sample would need to behave strategically to generate these empirical results. Second, the observed patterns would have to occur according to chance alone in order to generate spurious correlations with the randomly assigned shopper script. With a relatively large number of

[56]However, the drug quality index is inconclusive, as the upper bound switches sign.

villages and outlets, this is less likely. Finally, the analysis of additional data collected show that these quality differences are not driven by price or cost differentials by brand of drug.

Additional evidence suggests that drug quality is unobservable to consumers. Many of the drugs with public sector markings were bent to make the stamp less noticeable, or the stamp was partly rubbed off. I compare the distribution of failing tablets to the medical effectiveness of completing a partial dosage, compared to a full dosage (not shown). The medical literature suggests that in the short-term, a patient who has malaria is likely to feel better so long as they consume at least 16 tablets.[57] The average dose response is consistent with the observed bimodal distribution of the number of substandard tablets within a failing dosage. I estimate that 57 percent of failing samples have enough *passing* tablets that the patient would likely still have their malarial episode temporarily cured. In other words, substandard medicines are more accurately thought of as diluted high-quality drugs than dosages of sugar pills [Atukunda and Fitzpatrick, 2015].[58]

7.5 Provider Effort

In Table 10, I estimate whether provider effort changed in response to customer information. First, following Das et al. [2013], I test whether providers abide by a "checklist" of proper behavior. According to official guidelines, providers should first administer a malaria test prior to dispensing antimalarial medicines. 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. Evidence from both developed and developing countries indicates that patients care about whether health outcomes improve, but also about 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 these principles to the antimalarial health market. I test whether the shoppers feel that they are given adequate attention, that the provider

[57] More precisely, the medical literature suggests that the final 8 tablets of the full adult dosage are no more effective at immediately improving health, but rather reduces the likelihood of a return infection of the same parasite over the next month by 18 percent [Van Vugt et al., 1999].

[58] Of course, that estimation is rough and is dependent on a number of assumptions. Namely, whether the individual actually does have malaria, the individual's malarial resistance level, diet, the presence of vomiting in the current malarial episode, and the order of which the tablets were consumed would all likely affect the effectiveness of a given dosage.

explained all of the available options, and that the provider was friendly. Results suggest that providers respond to increased shopper information by exerting lower effort and decreasing 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 the provider adheres to the official guidelines. Providers are 4.4 percentage points less likely to express doubts that the patient truly has malaria when shoppers show either the diagnosis or the appropriate treatment. They are 8.2 percentage points less likely to do so when customers know both the disease and the treatment. Furthermore, providers faced with a customer who knows either disease or treatment are 6.8 percentage points less likely to advise that the patient take a malaria test. The number jumps to 15.8 percentage points when the customer has both knowledge of diagnosis and treatment. Shoppers with any information are 4.7 percentage points less likely to report that the provider asked any questions regarding the patient's health, and again, the number rises to 9.7 percentage points when the customer knows both the diagnosis and the treatment. Shoppers reciting scripts in which they know either the diagnosis or appropriate treatment also report that providers put forth lower subjective measures of effort. 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. Amassing these variables into an index, shoppers showing information rate vendors' service quality 0.126 standard deviations lower. Results are robust to a wide range of specifications and samples.[59]

[59]Note that providers could assume that customers with information do not want such advice or questioning, or assume that less was required of them. I interpret both of those motivations as consistent with both the model and theoretical analysis. However, as health professionals they are expected to act in the interest of the patient's and the public health.

8 Mechanisms: Reputation Effects and the Value of Service Quality

While the experimental results show that prices and quality change in response to customer information, they do not explain how or why price and quality differentials can persist within a market. In this section, I use two different approaches to identify plausible mechanisms driving the experimental results. First, I estimate hedonic regressions of price on quality from the experimental data to show that there is a service quality, but not a drug quality, "premium." These results explain why customers within the market do not necessarily find it optimal to declare that the patient has malaria (a commonly known disease). Although customers would enjoy a 5 percent price decrease, customers would also experience lower service quality, a valued attribute of the good. Second, I analyze additional survey data from real customers, testing the key assumptions of the conceptual model. The results suggest that information may signal to providers additional characteristics regarding consumer demand. In particular, providers may believe customers with more information are less likely to return to the outlet and less likely to value good service. Providers would then strategically allocate lower quality drugs to customers where the reputation incentives are weaker.

8.1 Importance of Service: Hedonic Models

One difficulty is that price, quality, and service quality are all different outcomes but measured during the same transaction. As a result, the changes in outcomes may be correlated. For example, if price and drug quality were correlated then it would be hard to justify drug quality as unobservable at the time of purchase; similarly, a price differential could persist in the market if it is related to service quality, and may reflect the market valuation of good service. Using data from the experimental analysis, I analyze these issues by estimating hedonic regressions:

$$PricePaid_{st} = \zeta_0 + \zeta_1 ServiceQuality_{st} + \zeta_2 DrugQuality_{st}\gamma_v + \chi' X + \epsilon_{st} \tag{8}$$

Results in Table 11 support the interpretation that providers increase the price charged based upon the effort/service quality that they give. For each additional standard deviation of the service quality index, the average price paid increases by \$0.36. The service quality index is significantly and positively correlated with the price paid, although measures of drug quality are not correlated with the price paid. These results imply service quality is observable and valued on the margin; drug quality, as an unobservable measure of quality, cannot adequately be priced in the market. This finding is robust to a log price specification, using the price index as an outcome, and controlling for drug fixed effects.

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 suggests why the majority of customers continue to ask for provider opinions, even though there are price decreases from presenting information. If price falls at the expense of good service, customers may simply not find it optimal to invest in information.

8.2 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, such as wealth, the likelihood of using preventive measures, or the likelihood of returning to the outlet. Therefore, I use additional data collected from real customers to estimate what demand characteristics are also 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.

First, I analyze whether the correlation of information with transaction outcomes is of the same sign as that found in the experiment. Results in Panel A of Table 12 show that customers with information do not differ in the likelihood of purchasing AL, but they are substantially less likely to report that the patient took a malaria test. They are less likely to buy an additional product, spend less money for the product, and have a lower total bill.[60] 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 must be negatively correlated with information and positively correlated with price, or vice versa.

Second, I look at demand characteristics associated with customer information to test if providers lower quality and lower price on the basis of observable characteristics. In particular, I examine characteristics that are correlated with treatment-seeking and potential reputation incentives, such as repeat visits: income, education, and being a repeat customer. Results in Panel B show that there is only one characteristic with a statistically significant correlation with information: 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. While counterintuitive that customers appear to repeatedly visit providers and ask for information about their purchases – in other words there is little learning about health taking place– this pattern is consistent with previous research in the health market [Ingham and Miller, 1983, Das and Hammer, 2014]. In contrast, the other potential characteristics that may be correlated with both demand characteristics and/or information- such as distance, preventive health behaviors, household characteristics, and gender– are not found to be significantly correlated.

Finally, I adapt the specification in Equation (7) to examine the robustness of this interpretation. Specifically, I examine the link between information and the value of customer service. Real customers were asked where they typically shop, and why they choose this particular store for their purchase that day.

$$Y_{st} = \lambda_0 + \lambda_1 AnyInformation_{st} + \gamma_v + \psi' X + \mu_{st} \tag{9}$$

where $AnyInformation$ is a dummy variable indicating that the real customer either knew their diagnosis or asked for a specific product.[61] I test whether information is correlated with

[60] 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.

[61] I do not differentiate between asking for AL specifically and asking for a different drug or brand.

the value placed on good service, controlling for whether the patient was an adult, income, years of education, and village fixed effects. Results in Table 13 show that customers with relatively more information are less likely to value a variety of customer service measures in choosing a store for their purchases.[62] For example, customers with information are 23.6 percentage points less likely to cite customer care as a reason for choosing that outlet for their purchase. Other reasons for choosing the outlet–cheap prices, convenience/distance, or good product selection–do not differ between customers with more or less information. This analysis is not consistent with different outside options by information revealed to providers. This analysis instead suggests that the two characteristics of demand negatively correlated with information are the likelihood of returning and the value of customer service. Both of these characteristics support the conclusions of the theoretical framework: customers with less information are more likely to purchase a high-quality drug, pay higher prices, and receive a higher service quality/effort.

8.3 Policy Implications

The problems of asymmetric information in healthcare and other markets for "experts" are well known. One strategy for correcting market failures is to empower patients with increased information. Based upon comparing results from a symmetric information equilibrium to an asymmetric equilibrium leads to the conclusion that improved customer information improves customer welfare. However, this logic does not account for any potential strategic responses from providers to maximize profit, and assumes that customers can credibly signal a sufficient level of information to providers. In this paper, I show that information asymmetries are more difficult to correct than the standard model predicts.

There are three primary lessons for policymakers to consider as a result of this paper's conclusions. First, information campaigns may have direct effects on the market price and quality. In particular, providers recognize that not all people learn or "take up" information. In line with the existing evidence on other health campaigns,my results are consistent with a model in which certain demand groups are more likely to take up and utilize information at the point of sale than others. As a result, profit-maximizing providers use that information to price discriminate according to information, with different outcomes for different groups of

[62]Note that multiple responses were allowed.

consumers.

Second, decreases in quality limit the gains to consumers from learning and using health information. While price falls would be thought of as welfare enhancing for consumers, incorporating quality changes the welfare calculation. I show that unless quality is sufficiently correlated with information at the point of sale, quality may actually *decline* as a result of improved customer information. The documented falls in quality are important for understanding the welfare gains to information and rationalizing individual decision making. For individuals who strongly value service quality from their health providers, the net welfare gain from investing in increased information may be small. Therefore, it makes sense that uninformed customers do not find it optimal to invest in information if the result is lower service or lower drug quality. As a result, information gaps can persist, even for a common disease with a relatively simple treatment regimen.

Finally, improved customer information has limits on what it can accomplish, particularly in experience goods markets. The finding that information could potentially reduce price but may also reduce quality does not imply that individuals should be prevented from learning information about their purchases. My results suggest that information campaigns intended to empower customers regarding their purchases may have been somewhat successful at lowering prices for those consumers. In situations in which price is the primary barrier to utilization, my results suggest that an individual would be charged approximately 5.6 percent less.[63] Other types of policies, including increased regulation, would be necessary in order to improve drug quality and overall market functioning. However, my results are specific to the type of information varied. Information regarding prices, for example, could have a very different effect on the market.

9 Conclusion

Asymmetric information is a characteristic of health markets and other markets for experts. Understanding how to improve the functioning of such markets has implications for individual costs and societal health. One proposed solution to decrease information asymmetries is to

[63]It is difficult to translate this price reduction into increases in demand. Cohen et al. [2015] estimate that among adults, the price elasticity of demand is -0.318, implying a demand increase of only 1.8 percent. However, that is an out-of-sample prediction given the average prices in my data.

empower customers with information, potentially making customers less susceptible to fraud and quackery. However, existing research does not indicate how providers will respond to individual patients with more healthcare knowledge.

In this paper, I present results from a randomized audit study in the Ugandan antimalarial drug market to assess whether customers with more information pay different prices or receive drugs of a different quality. My findings suggest that providers respond to increased information through reducing prices, drug quality, and service quality. Prices for the recommended first-line malaria drug fall by approximately \$0.18. If, instead, shoppers had bought the product recommended by the provider, the price differential would have increased to \$0.27. In contrast, I find that drug quality *falls* by 3.4 percentage points in response to increased customer information. I also find substantial decreases in service quality in response to increased customer information.

I interpret these results through a model of price discrimination in an experience good market with two types of customers. All customers must decide whether to accept or reject their purchase without knowing quality at the time of purchase. Providers maximize profits over two periods, trading off the benefits of current period profits against the decrease in future profits if they sell a low-quality drug. Through this framework, I find that providers charge higher prices when they provide higher service quality, in order to ensure customers agree to purchase the drug. However, providers strategically allocate low-quality drugs to customers from whom they would be less likely to lose profits in the future, were low drug quality to be detected.

This study is an important contribution to the growing literature on markets with experience goods. Previous work has focused on situations where there are no information asymmetries, as in when doctors themselves need medical treatment. That work suggests that empowering customers should lead to improved quality, more appropriate care, and lower incurred costs. In contrast, I conclude that customers may have difficulty signaling credibly the same level of information as a provider at the time of purchase. Particularly in contexts with low levels of human capital and low levels of enforced regulation, consumers may continue be vulnerable to deception, even if they present relevant information at the time of purchase. More research needs to be done on problems of consumer deception worldwide, and whether results differ in non-health markets with experience goods. In this context, my results suggest that increasing consumer information does not necessarily improve welfare once quality is accounted for. Therefore, information should not be the a sole strategy for improving consumer and social welfare, but should be used in conjunction with other interventions to improve access to high-quality healthcare worldwide.

Figure 1: Project Timeline

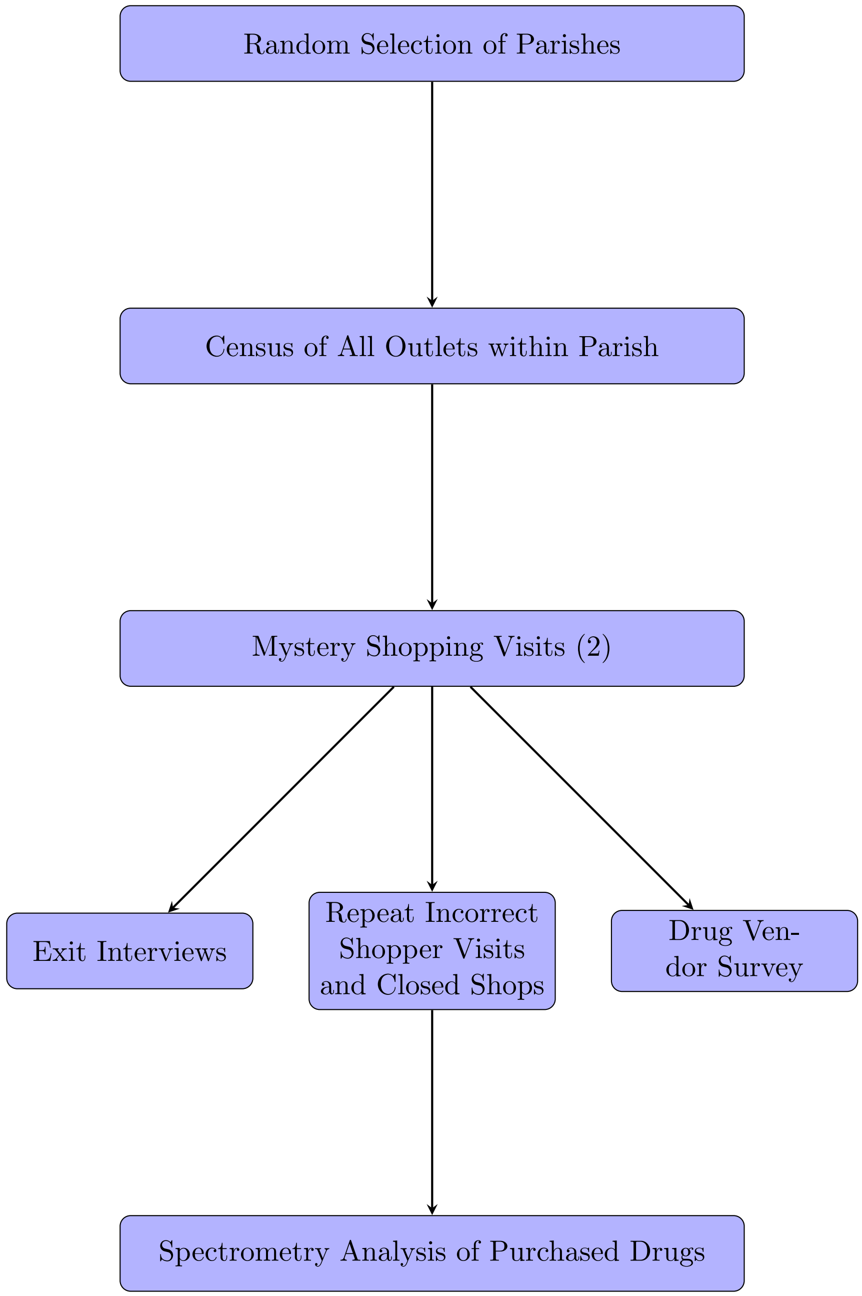


Figure 2: Experimental Protocol

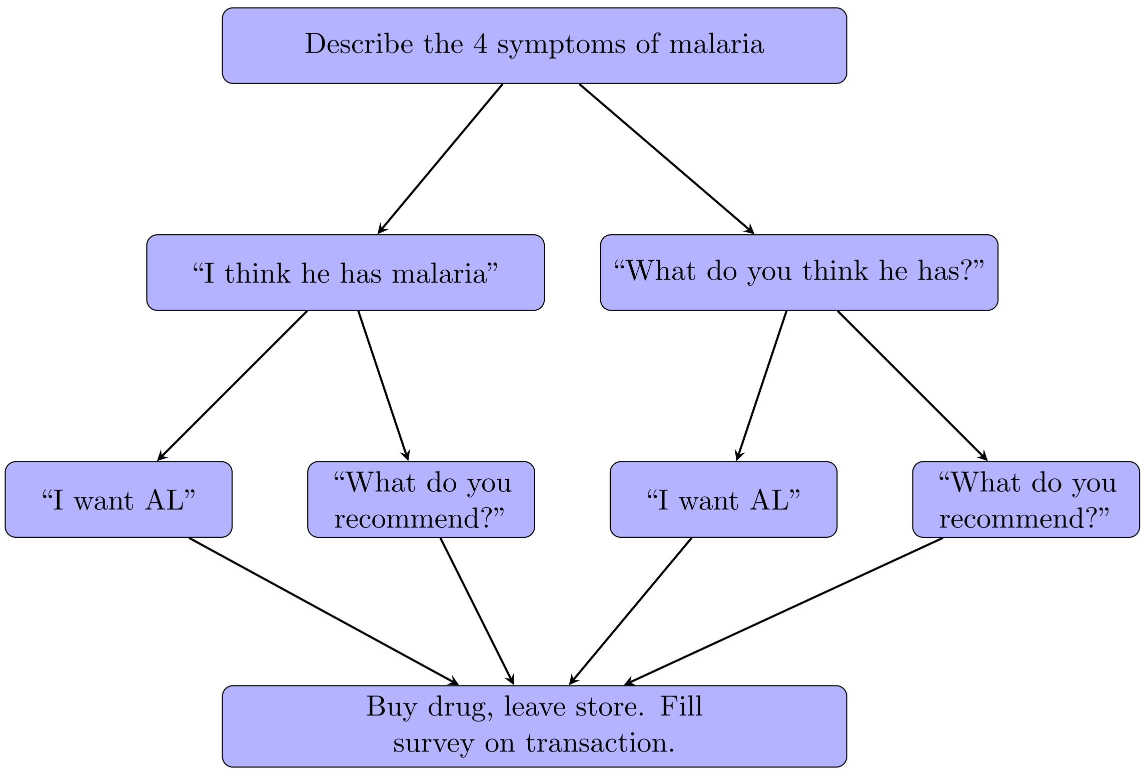
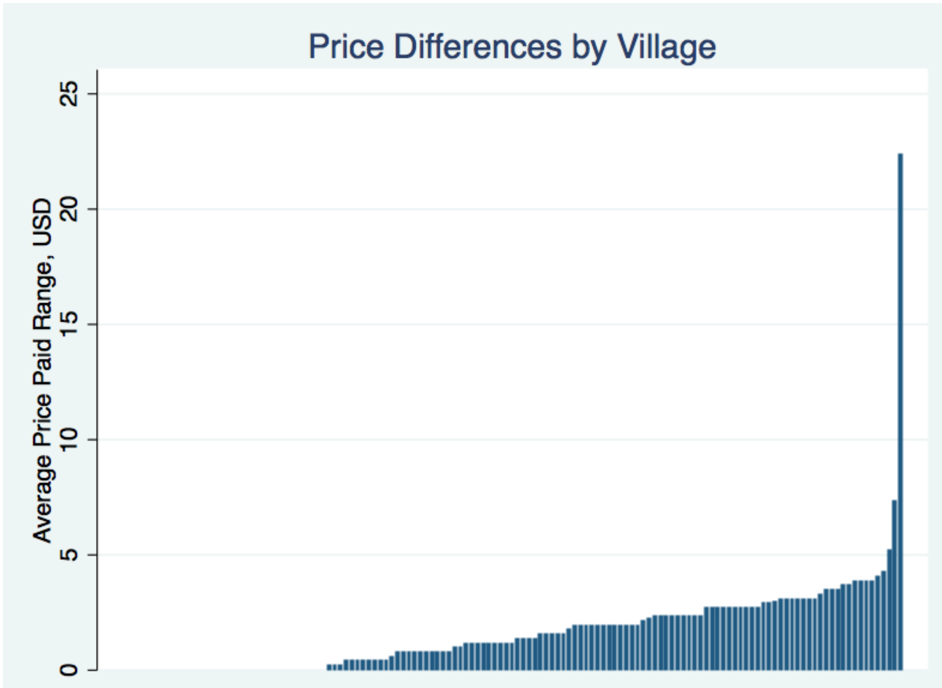
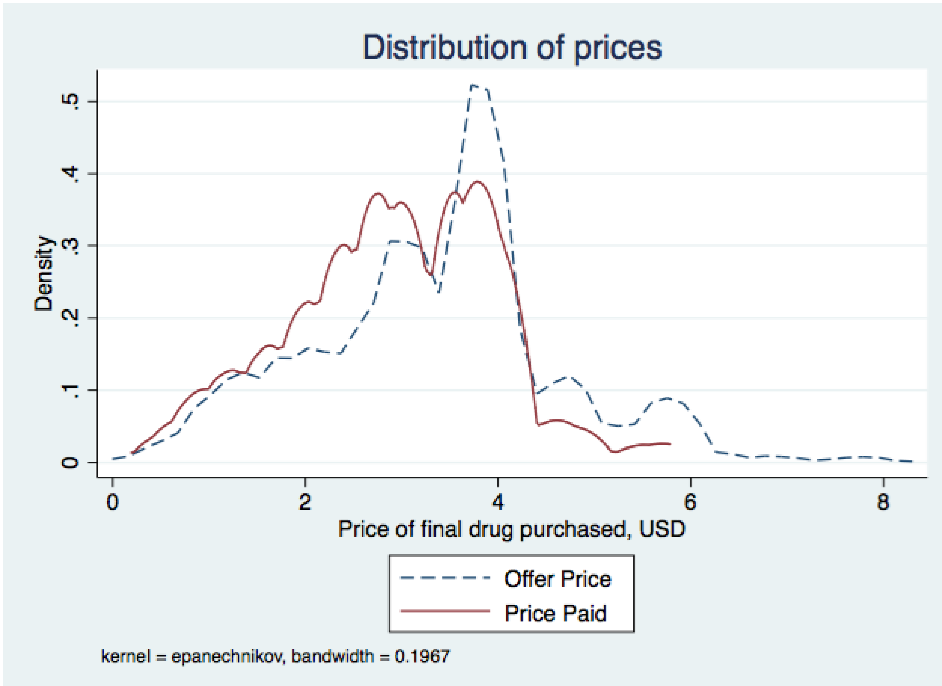


Figure 3: Price Dispersion



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.

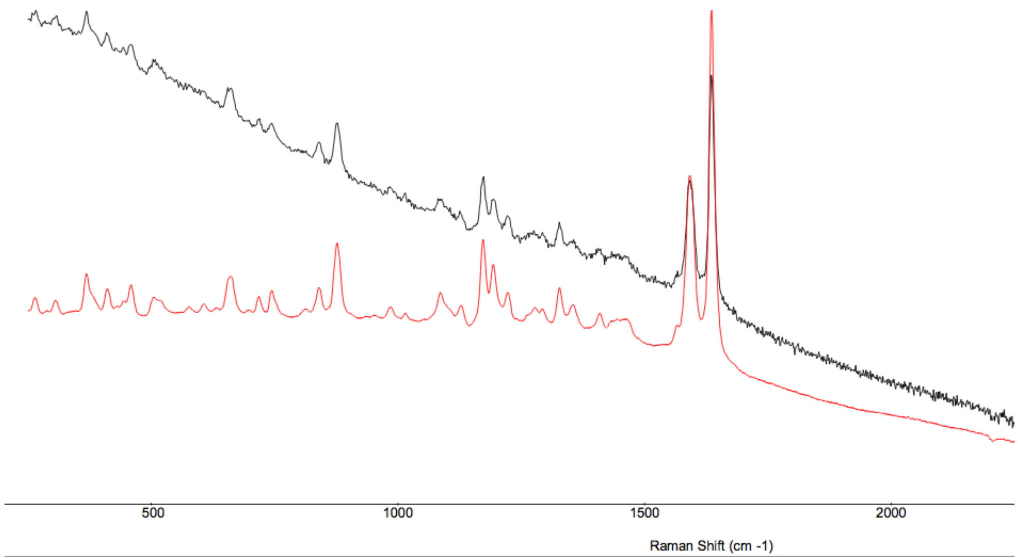
Figure 4: Price Distribution



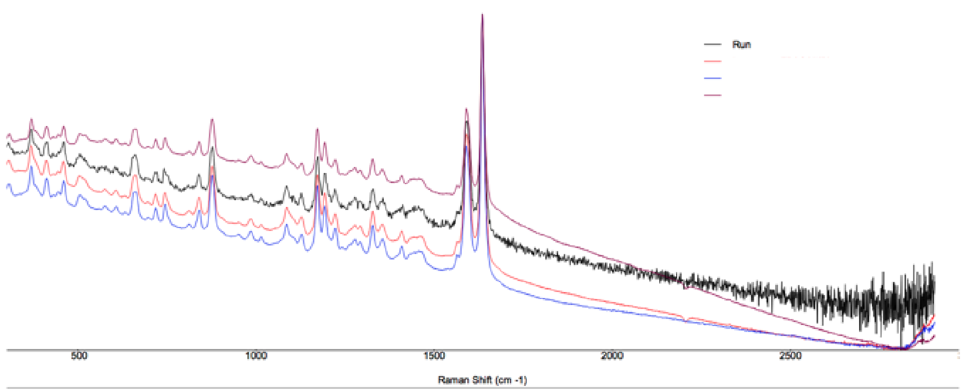
Notes: Above is the graph of the offer (pre-bargaining) and transaction prices (post-bargaining) for the final drug purchased, in USD. The exchange rate is \$1=2593 UGX. The sample is restricted to purchases of AL, and excludes high outliers values of the distribution, greater than \$10.00 (N=802).

Figure 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 darkest line is the Raman spectrum of the purchased tablet. In Panel A, the spectrum is compared against the spectrum of 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 spectra of all other brands. The purchased tablet does match the spectra of several other brands within the library. Thus, it is not considered substandard.

Table 1: Script Distribution and Study Design

	Ask for Diagnosis	Know Malaria	TOTAL
Ask for a Recommendation	Control 0.261 N = 230	Treatment 1: Know Only Malaria 0.248 N=218	448
Know AL	Treatment 2: Know Only Drug 0.250 N = 220	Treatment 3: Know Malaria & Drug 0.240 N = 211	431
TOTAL	450	429	879

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 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=2593 UGX.

Table 3: Summary Statistics of Provider Survey

Panel A: Vendor Characteristics	Average
Age	30.1
Male	0.230
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	21.8
Number of Customers Seeking Malaria Treatment	6.14
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	2.4
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	10.0

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. "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 4: Summary Statistics and Balancing: Analysis Sample

	All Visits	T1 Know Only Malaria	T2 Know Only Drug	T3 Know Malaria & Drug	Control No Information	Equal means test p-value: Cross-section	Village FE	Village & shopper FE
	(N=879)	(N=218)	(N=220)	(N=211)	(N=230)			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drug Shop	0.535	0.477	0.541	0.536	0.583	0.088*	0.035**	0.043**
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 (drug shop, clinic, or pharmacy) 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/Shopper" are binary variables indicating the gender of the drug dispenser or covert shopper. "Shop had no name" is a binary variable indicating whether the covert shopper noted on the survey that the shop had a displayed sign."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 the null of equal means between treatment groups in the cross-section. Column (7) contains the p-value from an F-test of the null of equal means between treatment groups, conditional on a village fixed effect. Column (8) contains the p-values from an F-test of the null 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 Drug	0.017	0.014	−0.019	−0.022	0.015	−0.380	−0.058
	(0.018)	(0.016)	(0.022)	(0.033)	(0.025)	(0.026)	(0.043)
T3:Know Malaria & Drug	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 Drug= 0	0.622	0.108	0.264	0.553	0.815	0.240	0.221
Observations	1016	1016	1016	1016	1016	1016	1016
R-squared	0.277	0.242	0.293	0.360	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 information of malaria are jointly zero. "P-value Drug=0" is the p-value from an F-test that the scripts indicating information of first-line treatment, AL, are jointly zero. "AL" refers to artemether-lumefantrine and "SP" refers to sulphadoxine-pyrimethamine. "Analysis Sample" 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, Analysis Sample (1)	Price Offered of Rec'd Option (2)	Ln(Price Offered) (3)	Price Index (4)
Any Information	−0.183∗∗	−0.269∗∗	−0.053∗	−0.081∗∗∗
	(0.093)	(0.111)	(0.030)	(0.031)
Panel B: Type of Information	(1)	(2)	(3)	(4)
T1:Know Only Malaria	−0.230∗∗	−0.143	−0.051	−0.081∗∗
	(0.116)	(0.139)	(0.034)	(0.039)
T2:Know Only Drug	−0.129	−0.284∗∗	−0.043	−0.070∗∗
	(0.107)	(0.124)	(0.039)	(0.034)
T3:Know Malaria & Drug	−0.192∗	−0.375∗∗∗	−0.066∗	−0.090∗∗
	(0.107)	(0.131)	(0.035)	(0.035)
Observations	879	869	879	879
R-squared	0.572	0.518	0.528	0.574
Number of Clusters	459	458	459	459
Pvalue Malaria= 0	0.110	0.013	0.137	0.032
Pvalue Drug= 0	0.193	0.012	0.172	0.029
Mean of Dep.	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 specifications contain village, shopper, and visit order fixed effects. All prices are in US Dollars. In Panel A, "Any information" refers to whether the covert 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. 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 Drug	-0.179	$-0.171*$	-0.102	-0.104
	(0.109)	(0.097)	(0.101)	(0.090)
T3:Know Malaria & Drug	$-0.269**$	$-0.254***$	$-0.210**$	$-0.223**$
	(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 Drug= 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 (N=984). The sample in Columns 3 and 4 is all visits in which a drug was purchased, the drug could be tested, and a profit margin could be calculated for the transaction. 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 covert 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 information of malaria are jointly zero. "P-value Drug=0" is the p-value from an F-test that the scripts indicating information 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 Drug	$-0.129*$	$-0.130***$	$-0.550***$
	(0.066)	(0.046)	(0.046)
T3:Know Malaria & Drug	$-0.159**$	$-0.177***$	$-0.686***$
	(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 Drug= 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 covert 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

Panel A: Any Information	Correct dosage (1)	Diverted Drug (2)	Counterfeit (3)	Substandard (4)	Fraction Substan-dard (5)	Drug Quality Index (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 Drug	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 & Drug	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 Drug= 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. "Fraction Substandard" is the fraction of the dosage sold that did not pass the spectrometry test and did not match any other samples in the spectral library. "Diverted Drug" is an indicator for whether or not the purchased dosage had public sector markings. "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 Drug	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 & Drug	−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	0.570	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 variable	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, very unfriendly, and 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: 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. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 12: Surveys from Real Customers

Panel A: Transaction Data	All Customers (N=372) (1)	Any Information (N=178) (2)	No Information (N=194) (3)	P-value of Difference (4)	P-value 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***
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). Regressions exclude missing values or responses of "I don't know". Column (2) refers to the sub-sample of the entire group of antimalarial customers who reported knowing either the diagnosis or the product they wanted at the time of purchase ("Any Information"). Column (3) refers to the sub-sample of the entire group of antimalarial customers who reported 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 from tests of the null that 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 paid for the primary antimalarial drug. Total bill is the total amount paid, inclusive of additional products. Repeat customer is a dummy variable indicating whether or not the customer reported buying from the shop before this purchase. 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. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 13: Real Customer Reported Reasons for Choosing Store

VARIABLES	Customer Service			Other Store Characteristics		
	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: Regressions are run on the sample of responses from real customers at study outlets purchasing antimalarial drugs. Respondents are classified according to their responses: whether they asked for a diagnosis, and whether or not they asked the vendor for a recommendation. Regressions exclude missing values or responses of "I don't know". All regressions contain village fixed effects and control for patient type (Adult or Child), Log Income (USD), and estimated years of completed education. Robust standard errors in parentheses, clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

References

. Press Release On Trade License Fees for Private Health Units . New Vision, July 2013.

A. Adhvaryu. Learning, Misallocation, and Technology Adoption: Evidence from New Malaria Therapy in Tanzania. Review of Economic Studies, 81(4):1331–1365, June 2014.

G. Akerlof. The Market for "Lemons": Quality Uncertainty and the Market Mechanism. The Quarterly Journal of Economics, 84(3):488–500, 1970.

M. L. Anderson. Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. Journal of the American Statistical Association, 103(484):1481–1495, Dec. 2008.

K. J. Arrow. Uncertainty and the Welfare Economics of Medical Care. The American Economic Review, 53(5):941–973, Dec. 1963.

E. Atukunda and A. Fitzpatrick. An Evaluation of Factors Affecting Antimalarial Drug Quality in the Retail Market. University of Michigan mimeo, pages 1–22, Mar. 2015.

J. K. Baird. Effectiveness of Antimalarial Drugs. The New England Journal of Medicine, 352 (15):1565–1577, Apr. 2005.

L. Balafoutas, A. Beck, R. Kerschbamer, and M. Sutter. What Drives Taxi Drivers? A Field Experiment on Fraud in a Market for Credence Goods. The Review of Economic Studies, 80(3):876–891, July 2013.

R. Bate, G. Z. Jin, and A. Mathur. Counterfeit or Substandard? The Role of Regulation and Distribution in Drug Safety. NBER Working Paper 18073, pages 1–34, May 2012.

D. Bennett and W. Yin. The Market for High-Quality Medicine. NBER Working Paper 20091, pages 1–59, Apr. 2014.

M. Bjorkman, J. Svensson, and D. Yanagizawa-Drott. Can Good Products Drive Out Bad? Experimental Evidence from Local Markets for Antimalarial Medicine in Uganda. Stockholm University Working Paper, pages 1–47, Aug. 2012.

B. J. Bronnenberg, J.-P. Dube, M. Gentzkow, and J. Shapiro. Do Pharmacists Buy Bayer? Informed Shoppers and the Brand Premium. NBER Working Paper 20295, pages 1–51, June 2014.

A. Chandra, D. Cutler, and Z. Song. Chapter Six. Who Ordered That? The Economics of Treatment Choices in Medical Care. In Handbook of Health Economics, pages 397–432. Elsevier B.V., Dec. 2011.

J. Cohen, P. Dupas, and S. Schaner. Price Subsidies, Diagnostic Tests, and Targeting of Malaria Treatment: Evidence from a Randomized Controlled Trial . American Economic Review, 105(2):609–645, Feb. 2015.

Commission, Federal Trade and US Department of Justice, US Department of. Horizontal Merger Guidelines. Technical report, Aug. 2010.

C. Comoro, S. E. D. Nsimba, M. Warsame, and G. Tomson. Local Understanding, Perceptions Snd Reported Practices Of Mothers/Guardians and Health Workers On Childhood Malaria In A Tanzanian District—Implications For Malaria Control. Acta Tropica, 87(3):305–313, Aug. 2003.

J. Currie, W. Lin, and W. Zhang. Patient Knowledge and Antibiotic Abuse: Evidence From An Audit Study In China. Journal of Health Economics, 30(5):933–949, Sept. 2011.

M. Darby and E. Karni. Free Competition and the Optimal Amount of Fraud. Journal of Law and Economics, 16(1):1–23, Apr. 1973.

J. Das and J. Hammer. Quality of Primary Care in Low-Income Countries: Facts and Economics. Annual Review of Economics, (10):11–46, Feb. 2014.

J. Das, A. Holla, M. Kremer, and K. Muralidharan. Quality and Accountability in Health: Audit Evidence from Primary Care Clinics in India. World Bank mimeo, pages 1–60, 2013.

S. de Mel, D. J. McKenzie, and C. Woodruff. Measuring microenterprise profits: Must we ask how the sausage is made? Journal of Development Economics, 88(1):19–31, Jan. 2009.

W. Deressa, A. Ali, and F. Enqusellassie. Self-Treatment of Malaria in Rural Communities, Butajira, Southern Ethiopia. Bulletin of the World Health Organization, pages 1–10, 2003.

W. Deressa, A. Ali, and D. Hailemariam. Malaria-Related Health-Seeking Behaviour and Challenges for Care Providers in Rural Ethiopia: Implications for Control. Journal of Biosocial Science, 40(01), Jan. 2008.

A. Dillon, J. Friedman, and P. Serneels. Health Information, Treatment, and Worker Productivity: Experimental Evidence from Malaria Testing and Treatment among Nigerian Sugarcane Cutters. IZA Discussion Paper No. 8074, pages 1–47, Mar. 2014.

D. Dranove. Demand Inducement and the Physician/Patient Relationship. Economic Inquiry, 26(2):1–18, Apr. 1988.

D. Dranove, D. Kessler, M. McClellan, and M. Satterthwaite. Is More Information Better? The Effects of "Report Cards" on Health Care Providers. Journal of Political Economy, 111 (3):555–588, Apr. 2003.

R. G. Evans. Supplier-induced Demand: Some Empirical Evidence and Implications. The Economics of Health and Medical Care, 6:162–173, June 1974.

S. Godlonton, A. Munthali, and R. L. Thornton. Responding to Risk: Circumcision, Information, and HIV Prevention. Review of Economics and Statistics, pages 1–50, May 2014.

T. N. Hubbard. How Do Consumers Motivate Experts? Reputational Incentives in an Auto Repair Market*. The Journal of Law and Economics, 45(2):437–468, Oct. 2002.

J. G. Ingham and P. M. Miller. Self-Referral: Social and Demographic Determinants of Consulting Behavior. Journal of Psychosomatic Research, 27(3):233–242, Mar. 1983.

M. Jacobson, C. C. Earle, M. Price, and J. P. Newhouse. How Medicare's Payment Cuts For Cancer Chemotherapy Drugs Changed Patterns Of Treatment. Health Affairs, 29(7): 1391–1399, July 2010.

B. M. Jennings, S. L. Heiner, L. Loan, E. Hemman, and K. Swanson. What Really Matters to Healthcare Consumers. The Journal of Nursing Administration, 35(4):173–180, Apr. 2005.

E. M. Johnson and M. M. Rehavi. Physicians Treating Physicians: Information and Incentives In Childbirth. NBER Working Paper No. 19242, pages 1–58, Jan. 2014.

T. Kelesidis, I. Kelesidis, P. I. Rafailidis, and M. E. Falagas. Counterfeit Or Substandard Antimicrobial Drugs: A Review Of The Scientific Evidence. Journal of Antimicrobial Chemotherapy, 60(2):214–236, June 2007.

J. Kling, J. Liebman, and L. Katz. Experimental Analysis of Neighborhood Effects. Econometrica, 75(1):83–119, Jan. 2007.

J. T. Kolstad. Information and Quality when Motivation is Intrinsic: Evidence from Surgeon Report Cards. American Economic Review, 103(7):2875–2910, Feb. 2013.

J. Konde-Lule, S. Gitta, A. Lindfors, S. Okuonzi, V. O. Onama, and B. C. Forsberge. Private And Public Health Care In Rural Areas of Uganda. BMC International Health and Human Rights, 10(29):1–8, June 2012.

A. Kroeger and J. M. Hernandez. Health Services Analysis As A Tool For Evidence-Based Policy Decisions: The Case Of The Ministry Of Health And Social Security In Mexico. Tropical Medicine and International Health, 8(12):1157–1164, Dec. 2003.

M. E. Kruk and L. P. Freedman. Assessing Health System Performance In Developing Countries: A Review Of The Literature. Health Policy, 85(3):263–276, Mar. 2008.

D. S. Lee. Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects. The Review of Economic Studies, (76):1071–1102, 2009.

S. Levitt and C. Syverson. Market Distortions When Agents Are Better Informed: The Value of Information in Real Estate Transactions. The Review of Economics and Statistics, 90(4): 599–611, Nov. 2008.

M. Littrell, H. Gatakaa, I. Evance, S. Poyer, J. Njogu, T. Solomon, E. Munroe, S. Chapman, C. Goodman, K. Hanson, C. Zinsou, L. Akulayi, J. Raharinjatovo, E. Arogundade, P. Buyungo, F. Mpasela, C. B. Adjibabi, J. A. Agbango, B. F. Ramarosandratana, B. Coker, D. Rubahika, B. Hamainza, T. Shewchuk, D. Chavasse, and K. A. O'Connell. Monitoring Fever Treatment Behaviour and Equitable Access To Effective Medicines In The Context Of Initiatives To Improve ACT Access: Baseline Results And Implications For Programming In Six African Countries. Malaria Journal, 10(1):327, Oct. 2011.

M. Madajewicz, A. Pfaff, A. van Geen, J. Graziano, I. Hussein, H. Momotaj, R. Sylvi, and H. Ahsan. Can Information Alone Change Behavior? Response To Arsenic Contamination Of Groundwater In Bangladesh. Journal of Development Economics, 84(2):731–754, Nov. 2007.

M. Makanga and S. Krudsood. The Clinical Efficacy Of Artemether/Lumefantrine (Coartem®). Malaria Journal, 8(Suppl 1):S5, 2009.

T. G. McGuire. Chapter 9: Physician Agency. In A. Culyer and J. P. Newhouse, editors, Handbook of Health Economics, pages 462–517. Feb. 2000.

J. Meredith, J. Robinson, S. Walker, and B. Wydick. Keeping the Doctor Away: Experimental Evidence on Investment in Preventative Health Products. Journal of Development Economics, 105(C):196–210, Nov. 2013.

G. Nayyar, J. G. Bremand, P. N. Newton, and J. Herrington. Poor-quality Antimalarial Drugs In Southeast Asia And sub-Saharan Africa. The Lancet Infectious Diseases, 12(6):488–496, May 2012.

P. N. Newton, S. J. Lee, C. Goodman, F. M. Fernández, S. Yeung, S. Phanouvong, H. Kaur, A. A. Amin, C. J. M. Whitty, G. O. Kokwaro, N. Lindegårdh, P. Lukulay, L. J. White, N. P. J. Day, M. D. Green, and N. J. White. Guidelines for Field Surveys of the Quality of Medicines: A Proposal. PLoS Medicine, 6(3):e52, 2009.

F. Nuwaha. People's Perception Oof Malaria In Mbarara, Uganda. Tropical Medicine and International Health, 7(5):1–9, Apr. 2002.

K. A. O'Connell, H. Gatakaa, S. Poyer, J. Njogu, I. Evance, E. Munroe, T. Solomon, C. Goodman, K. Hanson, C. Zinsou, L. Akulayi, J. Raharinjatovo, E. Arogundade, P. Buyungo, F. Mpasela, C. B. Adjibabi, J. A. Agbango, B. F. Ramarosandratana, B. Coker, D. Rubahika, B. Hamainza, S. Chapman, T. Shewchuk, and D. Chavasse. Got ACTs? Availability, Price, Market Share And Provider Knowledge Of Anti-malarial Medicines In Public And Private Sector Outlets In Six Malaria-Endemic Countries. Malaria Journal, 10(1):326, Oct. 2011.

I. Okeke, A. Lamikanra, and R. Edelman. Socioeconomic and Behavioral Factors Leading to Acquired Bacterial Resistance to Antibiotics in Developing Countries. Emerging Infectious Diseases, 5(1):18–27, Jan. 1999.

C. E. Phelps. Diffusion of Information in Medical Care. Journal of Economic Perspectives, 6 (3):23–42, Aug. 1992.

H. Schneider. Agency Problems and Reputation in Expert Services: Evidence From Auto Repair. pages 1–44, Oct. 2007.

A. T. Sorensen. Equilibrium Price Dispersion in Retail Markets for Prescription Drugs. Journal of Political Economy, 108(4):833–850, Aug. 2000.

J. Stanback, M. Ottaviani, M. Bekiita, O. Nakayiza, and A. K. Mbonye. Injected with Controversy: Sales and Administration of Injectable Contraceptives in Uganda. International Perspectives on Sexual and Reproductive Health, 37(01):024–029, Mar. 2011.

Uganda Bureau of Statistics, ICF International. Uganda Demographic and Health Survey 2011 [FR264]. Technical report, 2012.

Uganda Bureau of Statistics, Uganda Malaria Surveillance Project National Malaria Control Programme and I. Macro. Malaria Indicator Survey (MIS). Technical report, Oct. 2010.

M. Van Vugt, P. Wilairatana, B. Gemperli, I. Gathmann, L. Phaipun, A. Brockman, C. Luxemberger, N. J. White, F. Nosten, and S. Looareesuwan. Efficacy Of Six Doses of Artemether-Lumefantrine (Benflumetol) in Multidrug-Resistant Plasmodium Falciparum Malaria. American Journal of Tropical Medicine and Hygiene, 60(6):936–942, Dec. 1999.

K. Xu, D. B. Evans, P. Kadama, J. Nabyonga, P. O. Ogwal, P. Nabukhonzo, and A. M. Aguilar. Understanding The Impact Of Eliminating User Fees: Utilization And Catastrophic Health Expenditures In Uganda. Social Science & Medicine, 62(4):866–876, Feb. 2006.

W. Yip. Physician Response To Medicare Fee Reductions: Changes In The Volume Of Coronary Artery Bypass Graft. Journal of Health Economics, 17:675–699, 1998.