Three Essays in Health and Development

by

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Dedication

I dedicate my dissertation to my parents and to my partner, Dusty. This journey would not have been completed without your continual love and support.

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Abstract

The quality of healthcare is low in developing countries. In this dissertation, I examine two different proposals to improve healthcare quality: improve customer information regarding healthcare choices, or enroll individuals in health insurance.

In Chapter 1, I present results from an audit study conducted in Uganda. I compare the price paid and the drug quality received between shoppers in the same village who either ask for a diagnosis (or declare the patient has malaria) or ask for a drug recommendation (or ask for a specific product. I find that shoppers who present information about either the diagnosis or recommended treatment pay approximately $0.18 (5 percent) less. Counter-intuitively, I find that customers who present information about either the diagnosis or the recommended treatment are 3.4 percentage points more likely to be sold a substandard drug. I develop a conceptual model to justify my findings and conclude that improved information will not improve quality in a market if information and detection of low quality are not sufficiently related.

In Chapter 2, coauthored with Esther Atukunda, we present descriptive analyses from the same data collected in Uganda. We combine data from drug outlets, covert shoppers, and real customers to test hypotheses of how low quality drugs enter a market. We estimate that only 3.4 percent of purchased drugs are substandard: a much higher drug quality than found in previous studies. We develop three stylized facts: substandard medicines are typically diluted high-quality medicines; customers cannot tell which drugs are low quality; and vendors are complicit in the sale. We end with a discussion of policy interventions.

In Chapter 3, coauthored with Rebecca Thornton, I present results from an experiment conducted in Nicaragua that randomly allocated health insurance subsidies to parents. We specifically examine differential effects among children who were part of an insured household, but ineligible for health insurance themselves due to an age restriction. Our results indicate that the health insurance significantly increases access to higher-quality providers and altered the entire family's health demands. In particular, eligible, insured children substantially increase healthcare utilization, while ineligible children in insured households decrease healthcare visits.

Chapter 1: Do Informed Consumers Reduce the Price and Prevalence of Counterfeit Drugs? Evidence from the Antimalarial Market

1.1 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?

Asymmetric information may contribute to the widespread prevalence of low-quality healthcare in developing countries. 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).[1] 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 qual-

[1]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.

ity 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 to an exogenous change in financial incentives by comparing differences in caesarean section rates following a change in reimbursements at HMO hospitals when physician-patients give birth compared to when non-physician patients give birth.[2] Related literature in non-healthcare markets with "experts" finds similar differences between prices paid by experts and the general population.[3] 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 im-

[2]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).

[3]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.

prove the quality of treatments given to patients due to intrinsic motivation to beat the competition. Using a very similar policy experiment, 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 Greek 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 challenge. 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. These 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 the absence of random assignment. 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 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 on average 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 customer type is common knowledge. For each group, firms trade off current benefits from selling a "bad" drug against the potential reduction in future profits 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 customer type dictate the optimal choice of quality. I then consider where customer 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.[4] Despite malaria's prevalence, misconceptions are common, and there is substantial 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 in response to improved customer information in my model 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 WHO guidelines, 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

[4]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).

testing availability, only half of covert shoppers were advised to have the patient take a malaria test. Finally, 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 chapter 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.

1.2 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 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.

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. The average child has approximately two episodes per year, and the average adult has an episode approximately every other year (Uganda Bureau of Statistics, Uganda Malaria Surveillance Project National Malaria Control Programme and Macro, 2010).

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).[5]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).

[5]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 (Okwi et al., 2010).

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-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).[6]

It is also unknown which interventions are the most cost-effective for improving drug quality. Recent studies with large 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.

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.

[6]For a review of the existing literature, see Kelesidis et al. (2007) or Atukunda and Fitzpatrick (2015)

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 approximately 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 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).[7] 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.[8] There are no studies to my knowledge demonstrating that information regarding diagnosis or appropriate treatment affect economic outcomes.

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).[9] 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 response to problems of distribution through the public health sector,

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

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

[9]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).

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 of drug shops and medical clinics, with some pharmacies.[10] 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.[11] 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).[12]

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, $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.[13] However, first-line treatment is still unaffordable for

[10]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).

[11]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.

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

[13]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

many people. For example, the price of AL in my data is $3.19, three times higher than the target price of approximately $1.[14] There are no price regulations on medicines in Uganda.

1.3 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 1.1 contains the project timeline. In this section, I describe the experimental methodology and study protocol.

1.3.1 Sample Selection

Data was collected from 45 randomly selected parishes within 5 districts.[15] Study team members then conducted a census and mapped all drug outlets - primarily drug shops, clinics, and pharmacies - within study parishes with

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.

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

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

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. Online Appendix A describes the power calculations informing the design, and Online Appendix B describes how the analysis sample was created. Additional details are also in Atukunda and Fitzpatrick (2015).

1.3.2 Experimental Design

The experimental design is pictured in Table 1.1 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.[16] 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.[17] Then, shoppers either 1) said that they think that the patient

[16]Scripts were carried out in local language at the discretion of the shopper, aside from in Kampala and Busia where English was used occasionally.

[17]The patient was also randomly assigned independently of the shopper scripts. The

has malaria, or 2) asked for a diagnosis, to which there was nearly always a response of "malaria".[18] Shoppers then either 1) asked for artemether-lumefantrine (AL), the WHO-recommended first-line treatment of malaria, or 2) asked for a drug recommendation.[19] A picture of the protocol is in Figure 1.2. Additional details related to training and shopper behavior are outlined in Online Appendix F.

Drug Purchases

All shoppers were given $3.86 (10,000 UGX) in small denominations of used-looking money to pay for all transactions.[20] 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.

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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 the shopper in all specifications, and the coefficient on the dummy is statistically insignificant in nearly all specifications.

[18]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.

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

[20]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.

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 included if another drug was recommended, the price of the recommendation, and other products offered. The total number of antimalarial options and details on up to three options 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 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.

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. In practice, results are slightly stronger when the final 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.[21] It is not expected

[21]First, shoppers could buy a half dose, report buying a full dose, and pocket the

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 bias. This is unlikely, because neither shoppers nor supervisors were told the study expected to find price or quality differences between different scripts.[22]

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 re-

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.

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

maining 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).

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^{TM} RM.[23] 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

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

library" for the study.[24] Each purchased tablet was tested at least once. Appendix E details the testing protocol, with additional information on storage and handling.

Analysis Sample

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.

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

[24]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.

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 1.3 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.[25]

1.4 Data & Descriptive Analysis

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

1.4.1 Drug Prices: Mean and Variance

During shopping, 933 drugs were successfully purchased in 1016 visits to outlets; 879 were able to be tested. Figure 1.4 graphically demonstrates that there is substantial price dispersion among antimalarial drugs within a

[25]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).

village, the variation that I use in the empirical analysis. Table 1.2 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. 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.[26]

Mean price differences mask the substantial variation in prices, even for the same type of drug. Panel B of Table 1.2 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 1.5. 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. 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

[26]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.

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.

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.

1.4.2 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 con-

straints.[27] 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.[28] As a result, there is an imbalance in the number of interviews per outlet. Online 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 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

[27]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.

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

consistent with real shopper behavior.

1.4.3 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 Online Appendix Table E3.

Table 1.3 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. Anecdotal evidence suggests this low rate is 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.[29] 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 information. On a standard test of malaria transmission knowledge, providers score an 81 percent compared to 72 percent among customers.

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

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 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.[30] The collected data also suggests that vendors have market power.

[30]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. For example, 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."

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). At the same time, consumers do have some degree of choice; only 6 percent are monopolists.

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 (45%) 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 was confidential. Third, due to the observed average differences in prices and costs by brand, I only consider exact matches by brand. Finally, although the 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 each brand at the parish level. Formally, the measure is

$$cost_{bp} = \sum_{i=1}^{N_p} c_{ibp} \tag{1.1}$$

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

$$profit_{tb} = price_{tb} - cost_{bp} \tag{1.2}$$

where profit varies at the transaction level t.[31] To measure *price* for transaction t of brand b, I use both the offer price and the transaction price. (The

[31]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.

offer price is the first price offered by the vendor before bargaining.) In Online Appendix B4, I present additional support for the validity of this measure of per-transaction profits.[32] It should be noted that this measure of cost as in Equation (1.1) 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.

1.5 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.[33] I focus on the provider's decision to sell "bad" drugs or "good" drugs, an attribute of the good that is unobservable to customers 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.

[32] 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.

[33] 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.

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, $e(s)$.[34] 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 and uninformed. I index customer type by $i \in \{I, U\}$. The customer's type is known. 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.[35]

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

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

[35] 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.

future sales, where the lost future sales can be thought of as a reputation cost to selling low-quality drugs.[36] 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 utility, but does affect the provider's future payoff.[37]

The Provider's Objective Function

The provider's problem can be written as follows:

$$\begin{aligned} \max_{p_i, s_i, q \in \{G,B\}} \quad & p_i - e(s_i) - c^q + \alpha_i^q \Pi_i(p_i) \\ \text{subject to} \quad & \theta s_i - p_i \geq 0 \end{aligned} \tag{1.3}$$

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.[38]

[36] 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).

[37] 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.

[38] 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

Customers of either type who are sold a bad drug never return; $\alpha^b = 0$.[39] I normalize the utility from the outside option to be 0 for both types.[40]

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.

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 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:

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, $\frac{\partial \Pi}{\partial p_i}\frac{\partial p_i}{\partial s_i} > \frac{\partial \Pi}{\partial e(s_i)}e'(s_i)$.

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

[40] 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).

$$\theta(1 + \alpha_i \Pi(\theta s_i)) = e'(s_i) \tag{1.4}$$

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

$$\begin{aligned} A + \alpha_i \Pi_i - c^G &\geq A - c^B \\ \alpha_i \Pi_i &\geq c^G - c^B \end{aligned} \tag{1.5}$$

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 good drug; otherwise, uninformed types are more likely to receive a good 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.[41] This is somewhat intuitive: a rational provider would not want to risk losing a loyal customer from whom they make high profits.

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 1.4, 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.

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

1.6 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.

1.6.1 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:

$$Y_{st} = \alpha_0 + \alpha_1 AnyInformation_{st} + \gamma_v + \delta' X + \epsilon_{st} \tag{1.6}$$

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 have the same interpretation. In order to control for unobserved variation across villages, I include γ_v, a village fixed effect.[42] 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 outlet level to account for any correlation of the error terms within outlets 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:

$$\begin{aligned} Y_{st} = \beta_0 + \beta_1 KnowOnlyMalaria_{st} + \beta_2 KnowOnlyDrug_{st} + \\ \beta_3 KnowMalaria\&Drug_{st} + \gamma_v + \delta' X + \epsilon_{st} \end{aligned} \tag{1.7}$$

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*"

[42] 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. An outlet 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.

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 scripts used for purchase differ from the assigned script. In Online 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 uncor-

related with other omitted variables specific to the transaction. The nature of the design made it difficult to collect characteristics on outlets prior to the shopper visits. Instead, I use objective observations and characteristics of the shopper's visit to test for systematic differences between treatment groups. These characteristics are unlikely to have been affected by the script, and are taken from the covert shopper data. Table 2.13 presents evidence that there are no systematic differences between scripts in the analysis sample. Online 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. In total, 42 percent of shops did not have a posted 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 2.13 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.[43]

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.[44] 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

[43]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.

[44]Details of training are in Online Appendix F.

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).

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 bounds (Lee, 2009) on point estimates from models that are conditional on making a purchase and being in the analysis sample as a robustness check; estimates are in Online Appendix Table E11.

Overall, 96 percent of attempts to purchase a drug resulted in the shopper

interacting with a shopkeeper. Unsuccessful visits typically occurred 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 1.5 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.[45]Appendix Table E13 shows that whether clinics and outlets charge consultation fees is the primary statistically significant of whether shoppers successfully made a purchase. Consultation fees are approximately double the cost of treatment (which the

[45]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 Online Appendix Table E12 for additional details.

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.

1.7 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.

1.7.1 Prices

Increased customer information decreases the price offered to shoppers for the same drug. Panel A of Table 1.6 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.[46]

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 pur-

[46]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 Online 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.

chased. 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.

The calculation of Lee Bounds in Online 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.

1.7.2 Profits

In Table 1.7, I test whether charging lower prices translates into lower profits. I find that customers with more information are lower profit-margin customers for vendors.[47] 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

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

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. Using the sample of purchases, as opposed to all visits, highlights that the effect of customer information on profits is not driven by whether or not a drug was purchased. Although estimates are slightly noisier, potentially due to fewer observations, results are similar. The difference in profits between treatment groups in the sample of purchases is similar in magnitude to the difference in price between treatment groups, and suggests 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.

1.7.3 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 antibiotics. Results in Table 1.8 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.[48]

1.7.4 Drug Quality

In Table 1.9, 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

[48]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.

customer at the time of purchase: whether the dosage had the correct number of tablets, and whether the pack has public sector markings ("diverted").[49] 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 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

[49] 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.

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 Online 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.[50]

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 substandard drugs to the covert shoppers. At a minimum only 6 percent of the sample would need to behave strategically to generate these empiri-

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

cal 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 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.[51] 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).[52]

[51]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 reduce the likelihood of a return infection of the same parasite over the next month by 18 percent (Van Vugt et al., 1999).

[52]Of course, that estimation is rough and is dependent on a number of assumptions: 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

1.7.5 Provider Effort

In Table 1.10, 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 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

which the tablets were consumed.

are 4.4 percentage points less likely to express doubts that the patient truly has malaria when shoppers know 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 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.[53]

1.8 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

[53]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.

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.

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 my experimental data, I analyze these issues by estimating hedonic regressions of the form:

$$PricePaid_{st} = \zeta_0 + \zeta_1 ServiceQuality_{st} + \zeta_2 DrugQuality_{st}\gamma_v + \chi' X + \epsilon_{st} \quad (1.8)$$

Results in Table 1.11 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 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 real 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.

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 1.12 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.[54] 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.

[54]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.

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 (1.7) 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.

$$Y_{st} = \lambda_0 + \lambda_1 AnyInformation_{st} + \gamma_v + \psi' X + \mu_{st} \tag{1.9}$$

where $AnyInformation$ is a dummy variable indicating that the real customer either knew their diagnosis or asked for a specific product.[55] I test whether information is correlated with 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 1.13 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.[56] 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.

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

[56] Note that multiple responses were allowed.

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. 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 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 calcula-

tion. 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.[57] Other types of policies, including increased regulation, would be necessary in order to improve drug quality

[57]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.

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.

1.9 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 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 1.1: Project Timeline

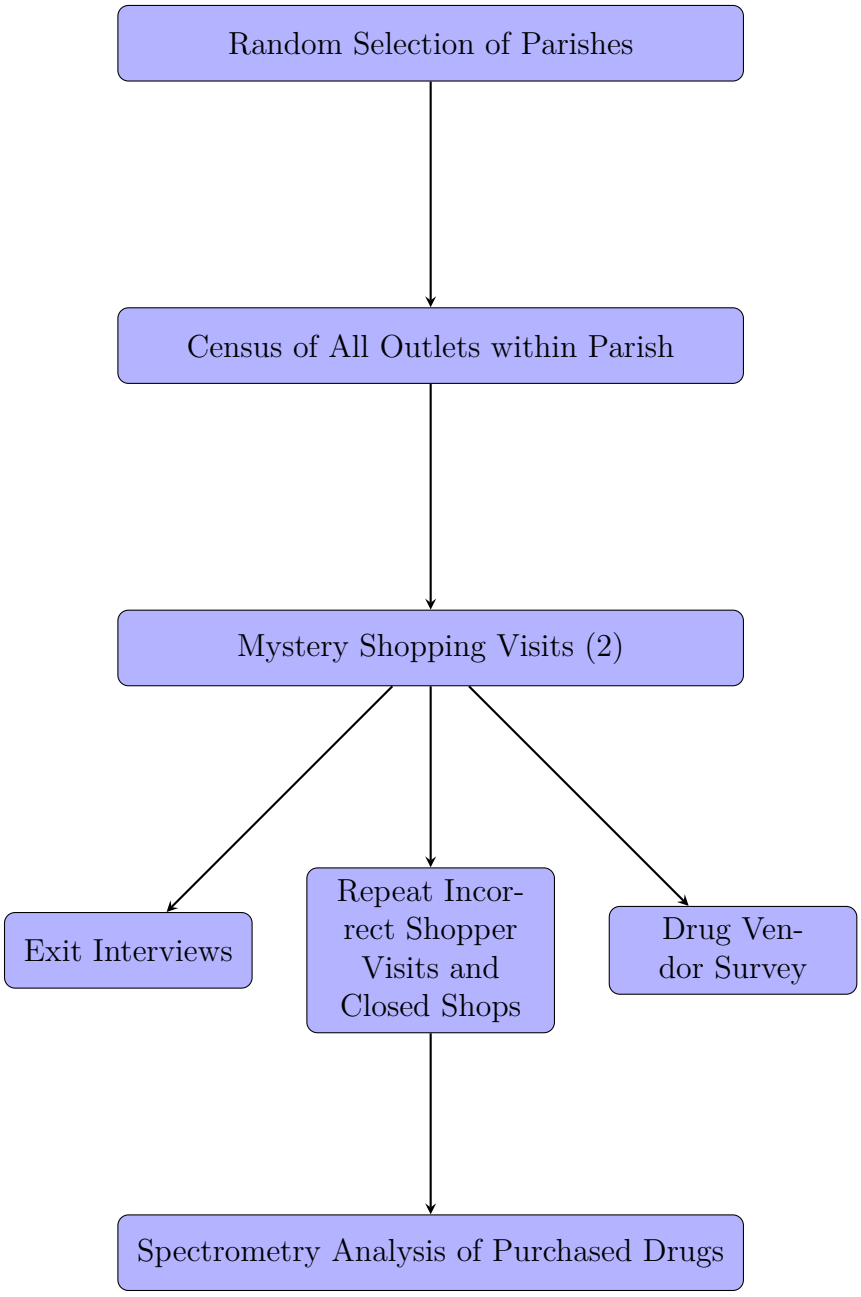


Figure 1.2: Experimental Protocol

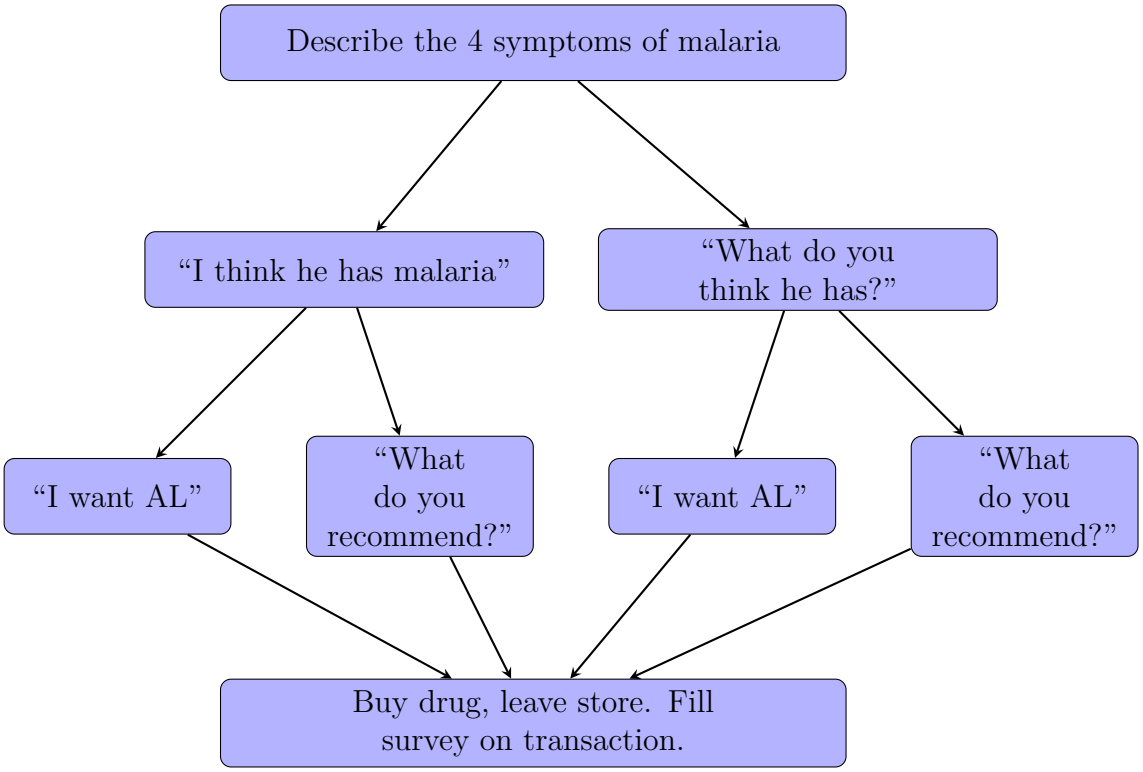
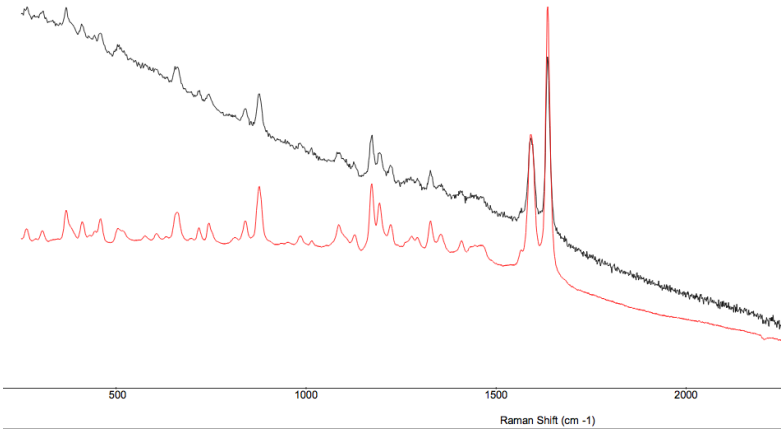
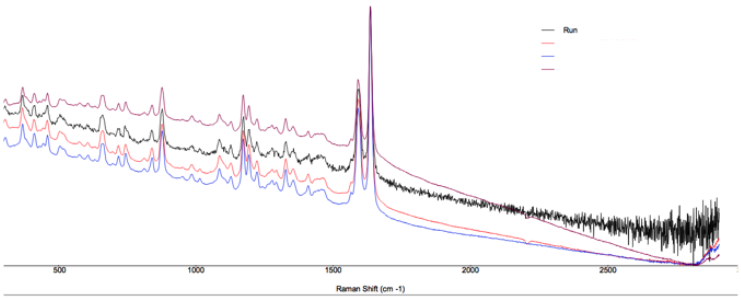


Figure 1.3: Demonstration of A Raman Spectrometry Scan

Panel A: A Counterfeit Scan

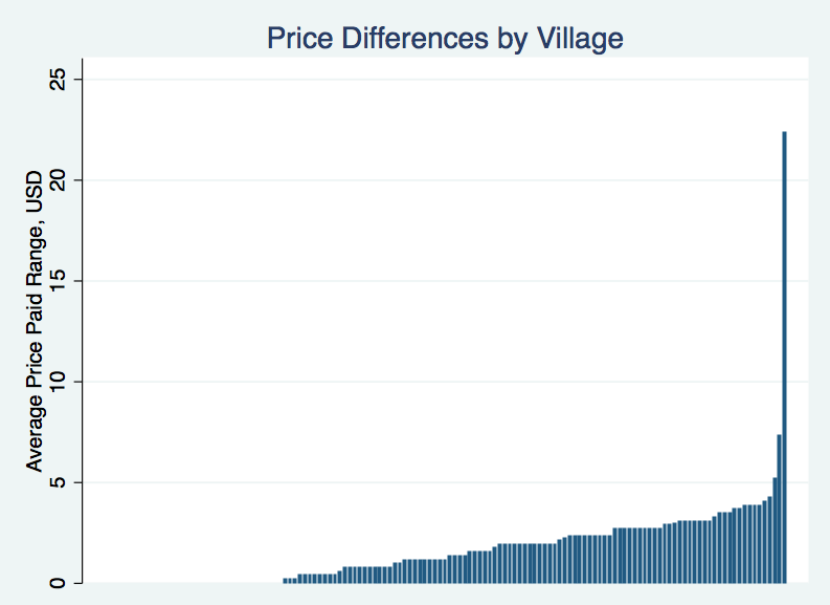


Panel B: Discovery Mode- Counterfeit, But Not Substandard



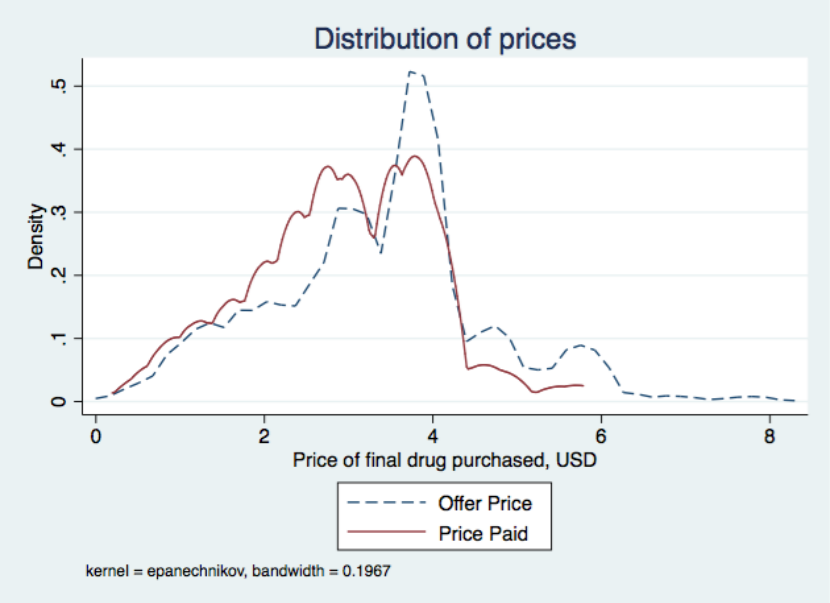
Notes: Raman spectroscopy works by blasting a molecule with an intense beam of light that causes the molecule's electrons to scatter in a specific fashion unique to the molecule. Above is a picture of the Raman spectra from a sample of AL that was classified as "Counterfeit but not substandard". In both 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 do not match. In Panel B, the spectrum is compared against the spectra of all other brands. The spectra matches.

Figure 1.4: Price Dispersion



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

Figure 1.5: 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 802 purchases of AL, and excludes 4 high outlying values of the distribution, greater than \$10.00.

Table 1.1: Script Distribution and Study Design

	Ask for Diagnosis	Know Malaria	TOTAL
Ask for a Recommendation	Control	Treatment 1: Know Only Malaria	
	0.261	0.248	
	N = 230	N=218	448
Know AL	Treatment 2: Know Only Drug	Treatment 3: Know Malaria & Drug	
	0.250	0.240	
	N = 220	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 1.2: 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 First-Line	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. Other first-line includes all brands listed as currently effective according to the Ugandan NDA. 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. Costs are averages of the reported of unit cost by brand within a parish.

Table 1.3: 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."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.

Table 1.4: Summary Statistics and Balancing: Analysis Sample

	All Visits	T1	T2	T3	Control	Equal means test p-value		
		Know Only Malaria	Know Only Drug	Know Malaria & Drug	No Information	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
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
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. Establishment type (drug shop, clinic, or pharmacy) is classified based upon the drug vendor census."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. 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 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 1.5: 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)
P-value Malaria = 0	0.814	0.042	0.081	0.557	0.339	0.238	0.098
P-value 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 1.6: 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
P-value Malaria= 0	0.110	0.013	0.137	0.032
P-value 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 1.7: 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)
P-value Malaria= 0	0.034	0.023	0.058	0.041
P-value 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 1.8: 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)
P-value Malaria= 0	0.023	0.001	0.000
P-value 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 1.9: Drug Quality

Panel A: Any Information	Correct dosage (1)	Diverted Drug (2)	Any Counter-feit (3)	Any Sub-standard (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)
P-value Malaria= 0	0.184	0.069	0.966	0.009	0.002	0.003
P-value 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 1.10: 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
P-value Malaria=0	0.103	0.000	0.010	0.000	0.012	0.517	0.000
P-value 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 1.11: 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 1.12: Surveys from Real Customers

	All Customers	Any Information	No Information	P-value of Difference	P-value With Village FE
	(N=372)	(N=178)	(N=194)		
Panel A: Transaction Data	(1)	(2)	(3)	(4)	(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***
Prim School or Less	0.253	0.281	0.228	0.244	0.270
Secondary School	0.445	0.449	0.443	0.7871	0.980
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 is 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 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. 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. 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 (excludes primary school). 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. 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. Statistical significance is determined clusters standard errors at the outlet level.$***p < 0.01, **p < 0.05, *p < 0.1$

Table 1.13: Real Customer Reported Reasons for Choosing Store

	Customer Service			Other Store Characteristics		
VARIABLES	Service	Knowledge	Speed	Cheap	Ease	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. $***p < 0.01, **p < 0.05, *p < 0.1$

Chapter 2: An Evaluation of Factors Affecting Drug Quality: Evidence from the Antimalarial Market in Uganda

2.1 Introduction

According to many different measures, the quality of healthcare is low in many developing countries. Providers lack required training, are unable to accurately diagnose ailments, and there is a substantial gap between provider knowledge and practice (Das et al., 2012; Das and Hammer, 2007; Leonard and Masatu, 2008). One measure of low healthcare quality is the prevalence of counterfeit drugs. According to a recent meta-analysis, between 12 to 50 percent of anti-malarial drugs sold in the private sector in sub-Saharan Africa are counterfeit, substandard or falsified (Nayyar et al., 2012). 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). Identifying ways to improve antimalarial drug quality– without raising prices– is important to improving the quality of healthcare, and ultimately health, in resource-poor countries.

Despite the substantial potential threat that low quality drugs pose to global health, there is a lack of sound empirical evidence on the prevalence rate of low-quality drugs. These limitations are because of substantial methodological challenges. The antimalarial drug market in low-resource countries is typically composed of informal establishments with loosely enforced regulation. Official records may be incomplete or inaccurate, and building a sample frame to estimate an "average" market rate of drug quality is difficult. The gold standard to measure drug quality– chemical assays to determine the percentage of active ingredients– are also time-consuming and expensive to conduct for a large number of samples. As a result of these challenges, the existing literature instead focuses on documenting that counterfeit and substandard drugs are found in a variety of countries and drug classes. Empirical work typically relies on small samples and non-random sampling methods. Therefore, little is known about what explains variation in drug quality rates within a country, whether price acts as a signal of quality or if shopkeepers are complicit in the sale of deceptively low quality drugs.

To address these limitations in the previous literature, we conduct a study with two primary objectives: 1) To estimate the average prevalence of low-

quality antimalarial drugs; 2) To ascertain what transaction, customer, and vendor characteristics are associated with low-quality drugs. We purchase 933 dosages from 438 outlets in randomly sampled areas of Uganda to estimate the average prevalence of counterfeit and substandard antimalarial drugs. We focus on artemether-lumefantrine (AL), the WHO recommended first-line treatment for uncomplicated malaria in Uganda. We concentrate on AL due to previous evidence of a high counterfeit rate for this drug and the significant health implications to consumers from ineffective treatment. We inspect and test all drugs using a handheld spectrometer, a device that is suitable for field studies and that can quickly test drugs for authenticity. This device also allows us to distinguish between two types of low-quality drugs: 1) counterfeit, yet medically effective drugs, and, 2) substandard medicines, those less likely to be medically effective. We link transaction data on the tested drugs with survey data from vendors at the outlets and real customers. This rich descriptive data allow us to examine supply and demand factors that are correlated with drug quality. We report results from survey modules on shop operations, low quality drugs, and survey exercises to estimate whether providers know they sell low-quality drugs.

Contrary to the existing literature, we find that drug quality is relatively high in the study area. While we find that counterfeit drugs are relatively common at 17 percent, we estimate only 4 percent of drugs are substandard. While we cannot generalize beyond the study area, or to other classes of drugs, it appears that estimates in the previous literature are an upper

bound on the rate of low-quality drugs. Our additional analysis of correlates leads to the three stylized facts regarding counterfeit and substandard drugs: 1) substandard low-quality drugs are typically diluted versions of high-quality drugs, as opposed to "sugar pills"; 2) substandard drugs are deceptive, and customers cannot distinguish substandard medicines from high-quality medicines; 3) a small number of vendors are complicit in the sale of low-quality drugs. However, identifying outlets and vendors that are more likely to sell low-quality drugs is difficult. Vendor behavior changes only slightly during low-quality drug sales. Observable characteristics of the establishment are generally not correlated with drug quality, and we reject the theory that degradation is a cause of low-quality drugs. We also find that areas with more competition have higher drug quality rates and that men are slightly more likely to be sold a substandard drug. Our data also support the interpretation that mobile drug hawkers are how substandard medicines infiltrate supply chains. We end with a discussion of potential policy interventions, including results from the vendors themselves on what would likely work to further improve drug quality rates.

While our data are extensive, there are some limitations in our analysis. Results are specific to the study setting and context. Although our data are from randomly selected areas, we document important geographic heterogeneity. Thus, even studies based on random sampling may find different average rates. We also caution that our empirical analysis on correlates should not be interpreted as causal parameters. We account for potential confound-

ing characteristics in our analysis, but there is likely bias due to omitted variables in our estimates. Finally, we are unable to measure seasonal for time-varying factors, or the drug quality rates of other drug classifications. Theses limitations highlight the pressing need for ongoing, large-scale studies of drug quality in important markets for global health.

This paper is organized as follows. In Section 2.2 we provide relevant background on antimalarial treatment and the Ugandan operating environment. 2.3 we provide the theoretical framework of our analysis, potential theories of how and why low-quality drugs end in markets. We next turn to describing how our study addresses each of these theories in Section 2.4, and describe the data that we collect. In Section 2.5 we present descriptive results and in Section 2.6 we outline our empirical estimating equation. In Section **??** we present our results on the correlates of low-quality drugs. We then discuss important mechanisms to interpret our results, namely if providers are complicit in the sale of low-quality drugs in Section 2.8. In Section 2.9 we conclude.

2.2 Study Background

We first outline the market for antimalarial treatment in Uganda. We discuss the choices that individuals have for antimalarial treatment. We conclude with an outline of the policies and laws relevant to the sale of low-quality drugs.

Healthcare in Uganda

All essential medicines, including antimalarial treatment, are available for free in public sector facilities. However, there are not enough facilities to meet the needs of the population. As a result, the public sector is characterized by long waiting times, poor service quality, and frequent stock-outs. There are also concerns of corruption and diversion of free medicines from public sector outlets for sale in the private sector. As a result of these problems in public sector distribution, the private sector is the first source of treatment for common diseases such as malaria.

As in many other markets of developing countries, the private sector for healthcare in Uganda is informal and loosely regulated. In Uganda specifically, individuals typically buy antimalarial medicines in the private sector, composed of nearly 17,000 drug shops and clinics, and 415 pharmacies (ACTwatch Group, PACE/Uganda & the Independent Evaluation Team, 2012). Despite their key role in healthcare delivery, vendors typically have inadequate medical qualifications. Stanback et al. (2011) estimates that up to 60 percent of drug vendors operate without the regulated medical qualifications and licenses, potentially contributing to the low levels of healthcare quality.

Anti-malarial Treatment in Uganda

In Uganda, malaria represents the number one burden of illness. It is endemic throughout the country. The recommended first-line treatment of

uncomplicated malaria is artemether-lumefantrine (AL) (ACTwatch Group, PACE/Uganda & the Independent Evaluation Team, 2012). AL is part of a larger class of medicines known as ACTs (artemisinin-combination therapies), and is over 95 percent effective in both adults and children (Baird, 2005). Quinine is another effective medicine, and commonly dispensed. However, is intended to be reserved as a second-line treatment and for complicated malaria (a severe form of malaria that can result in death, and primarily affects children). Older treatments– such as sulphadoxine-pyrimethamine (SP) – are widely available, and cheap, but are clinically ineffective due to parasitic resistance (ACTwatch Group, PACE/Uganda & the Independent Evaluation Team, 2012).

Work as recent as 2011 has found that AL is available at only 30 percent of outlets across six sub-Saharan African countries, including Uganda (O'Connell et al., 2011). This low rate of availability may be due to either low supply, low demand, or both. Stock-outs are reportedly common in the private sector, potentially due to inefficient stock management and poorly functioning supply chains. On the demand side, this low level of utilization is potentially due to high prices, low levels of caregiver awareness, or due to beliefs that low quality drugs are widespread. AL is a relatively newer treatment, and relatively expensive. In contrast to other sub-Saharan African countries, there is no regulation on prices in Uganda and few people have health insurance; thus, health care is paid nearly entirely out-of-pocket. Misconceptions regarding malaria transmission are common, and symptomatic

diagnosis from caregivers is problematic. Low-drug quality may also contribute to suboptimal utilization. If caregivers cannot tell the difference between high and low quality drugs, then standard economic theory predicts that households will be less willing to purchase drugs at all, potentially leading the market to collapse (Akerlof, 1970). As a result of these issues, is estimated that one-third of febrile ("symptomatic") children in Uganda do not receive first-line anti-malarial drugs (Uganda Bureau of Statistics, ICF International, 2012). Malaria is the second-leading cause of death among children under 5 in Uganda.

To increase the usage of essential medicines, there are large-scale manufacturing subsidies on select brands of AL under different global donor programs. While prices have fallen nearly by half since 2011, prices remain more than three times as high as the target price of the program (US$1).[58] These drugs are typically inspected for quality to ensure that minimum manufacturing standards are met. For example, the WHO pre-qualification program is intended to insure that the subsidized drugs that are distributed through governments and international agencies pass minimum quality standards.

[58]The effectiveness, and cost-effectiveness, of the subsidies at lowering prices is a subject of debate in global health. Studies generally find that the large-scale subsides of the AMFm program were effective at lowering prices (Tougher et al., 2012).

Relevant Ugandan Laws and Other Institutional Background

There are also institutions and policies in place to regulate drug quality. The government agency in charge of regulation is the Ugandan National Drug Authority (NDA). As part of this mandate, the NDA has undertaken initiatives to test imported drugs, license and regulate pharmacies and drug shops, contribute to consumer sensitization on the rational use of medicines, and raise awareness about the problem of counterfeit drugs. A recent audit covering the period 2006-2010, however, indicates that the agency overall is understaffed and under-funded to achieve these objectives.

In addition to poor regulation, there are weak criminal penalties for dealing in fake drugs.[59] As the problem of fake drugs has garnered attention, so have attempts to enact stricter legal penalties. In 2010, the Ugandan Parliament considered a law entitled "The Anti-Counterfeiting Goods Bill of 2010" that was intended to codify a maximum of 20 years of jail time for those convicted of trading counterfeit goods, and give more power to regulators. However, due to concerns over language, the bill has been tabled and is being revised in committees within Parliament. Part of the issue is that there is no international consensus for the definition of a counterfeit drug. There are concerns that under proposed laws, non-branded generics could become ille-

[59] A legal officer at UNBS has been quoted assaying that under current laws, the maximum penalty is two years imprisonment and a fine of 2000 shillings (approximately $0.81), however some individuals have been sentenced in Uganda for longer periods and/or paid larger fines (Mubiri, 2011).

gal. Thus, eliminating counterfeit drugs may unintentionally restrict access to medicines for the poor.

2.3 Theories of Low-Quality Drug Sales

In this section, we briefly outline various theories of how low quality drugs appear at outlets. We divide the various theories of low drug quality into three general categories: 1) demand-side factors, those factors that vary at the transaction-level; 2) supply-side factors, those that vary at the outlet-level; 3) institutional factors, including legal and social penalties, that vary at the either the outlet or market level. While some factors could arguably fit into several categories, our rough delineation will serve to guide the empirical analysis while keeping the unit of observation roughly the same within groups.

2.3.1 Demand-side Factors

The previous economics literature on low-quality drugs has focused on whether consumers can identify counterfeit drugs through signals, namely price. Bate et al. (2011) find in non-random samples from 17 countries that the price of antimalarial drugs is weakly and positively correlated with drug quality, and that the subjective shop appearance is also correlated with drug quality. Bjorkman et al. (2012) similarly find that the counterfeit drug rate within a non-random sample of project villages is weakly positively correlated with

price. These facts suggest that 1) price is a noisy signal of quality and 2) a low willingness-to-pay for quality of a drug, at least for the marginal consumer.

A complementary explanation for low-drug quality is that certain types of customers are more likely to purchase low-quality drugs than others. Numerous studies have documented that misconceptions about malaria causes and symptoms are widespread, and low average education levels may make customers more vulnerable to fraud. Bjorkman et al. (2012) also show that the counterfeit rate is positively correlated with the average village understanding of malaria transmission. In other words, shopkeepers take advantage of low information customers and differentially dispense substandard medicines to such groups. This theory can be generalized into a theory of either taste-based or statistical discrimination. Providers may simply not like individuals with certain characteristics, and selectively choose to give them low quality drugs. Alternatively, providers may make assumptions about demand characteristics on the basis of customer appearance or behavior. For example, providers may be able to guess an individual's knowledge or eduction level, or whether they are a local person, based upon gender or tribe of the shopper.

2.3.2 Supply-side Factors

Although a key source of healthcare in their communities, the private sector for medicines are also firms whose objective is to make profits. Vendors make choices of what drugs to stock, and when. As part of their decision, vendors must also consider how to maximize profits based upon input costs. There

are several different suppliers that vendors could use to procure new stock– such as other retail outlets, wholesale pharmacies, or mobile drug hawkers– and these suppliers may differ in their cost and quality of inventory. The informal nature of the market and lack of enforced regulation may make strategic behavior– such as selling cheaper, low quality drugs as high quality drugs– more likely. This theory implies that low drug quality is the result of vendors knowingly dispensing substandard drugs to unsuspecting customers to maximize profits.

However, counterfeiters are adept at mimicking licit packaging. Providers themselves could lack the ability to distinguish high quality from low quality drugs. Additionally considering potentially low shopkeeper business acumen, an alternative explanation may be that shopkeepers are deceived by suppliers and unwittingly dispense low-quality medicines. Similarly, shopkeepers could unintentionally sell low-quality drugs that have degraded over time due to improper storage conditions. For example, exposure to heat, direct sunlight, or humidity may cause active ingredients to degrade and become ineffective. All of these factors may contribute to low-quality drug prevalence.

2.3.3 Competition and Other Institutional factors

Other aspects of the operating environment may also affect the decision of a given provider to sell low-quality drugs. For example, firms may also compete over quality. Both Bennett and Yin (2014) and Bjorkman et al. (2012) randomly introduce competition into the medicine market; Bennett and Yin

(2014) randomizes chain store entry into urban areas of India and Bjorkman et al. (2012) randomize a high-quality NGO competitor into monopolistic villages in Uganda. Both find that the increase in competition causes an increase in drug quality.

In addition to private sector competitors, firms may also face competition from the public sector health facilities. Although shortages are reportedly common, if drugs are available for free in public facilities then competing over price is difficult.[60] Instead, firms may improve market drug and service quality to become more competitive instead.

A final salient factor may be the risks of legal or social penalties if the vendor was caught selling low quality drugs at an outlet. Laws as enforced make it difficult for legal penalties to be effective. However, customers may refuse to shop at the store. In addition, it is possible that drug vendors would be socially ostracized, confronted, or potentially become victims of vigilante justice. If these social sanctions vary by area, then perceived penalties of may explain varying drug quality rates.

2.4 Study Design

We collect a robust set of data to address these various theories of drug quality. Fieldwork took place from May-August 2013 and consisted of several

[60] Anecdotal evidence suggests that average quality falls when there are shortages in the market; counterfeiters then enter in droves, where there are profits and a lack of licit medicine. However, our data do not allow us to directly test this hypothesis.

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 an antimalarial drug according to a randomly assigned script. Third, additional survey data were collected from the drug dispenser at each outlet, and from real customers as they were exiting the outlet. Figure 1.1 contains the project timeline.

2.4.1 Study Sites

Uganda is composed of 112 districts that are each divided into counties.[61] Each county is further divided into subcounties; each subcounty is divided into parishes; each parish is then divided into villages.[62] Within each selected study district, we randomly selected two rural and two urban subcounties.[63] We then randomly selected two parishes within each urban subcounty and three parishes within each rural subcounty, totaling 10 total parishes in each of the five districts. For administrative reasons (such as fewer parishes in some subcounties) the study contains a total of 45 parishes, in which there are 142 villages with at least one drug outlet. We conservatively estimate that the study area covers drug vendors serving approximately 200,000 people.

Study team members then conducted a census and mapped all drug out-

[61] The total number of districts at the time of data collection was 112.

[62] According to the 2002 census, the average size of a parish is 4,625 people; the average size of a sub-county is 25,289. The average size of villages was not reported (Uganda Bureau of Statistics, 2008).

[63] Bushenyi, Busia, Mbarara, Rukungiri, and Kampala (the capital) were chosen as study districts due to their size and proximity to borders.

lets within study parishes with a corresponding physical description of the outside of the premises. I define drug outlet as "an immobile establishment that sells antimalarial drugs for profit."[64] The nature of this sampling strategy results in having a nearly complete picture of local antimalarial drug markets.

2.4.2 Drug Purchases and Testing

Following the recommendations of Newton et al. (2009), a "mystery" shopper was used to purchase medicines from these drug outlets.[65] The following protocol was used 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.

At the conclusion of the fieldwork, all purchased drugs were inspected by research assistants. The recorded drug characteristics include brand, ex-

[64]Note that this definition does not require that the establishment actually make a profit. The study also includes a small number of "other" types of outlets (e.g.) individuals who sell antimalarial drugs out of their homes, or shops that specialize in another market, such as hardware stores, but also sell antimalarial drugs. However, herbal shops are excluded from the sample frame, as are charitable or public sector hospitals or pharmacies.

[65]Shoppers used a randomized script to either declare that they have malaria or ask the shopkeeper for a diagnosis; then they either asked for a specific product or for what the shopkeeper recommends. There are significant observed differences with respect to both price and quality, and these results are reported in Fitzpatrick (2015).

piration date, number of tablets, and whether the drug had public sector markings ("diverted"). Drugs were then shipped to a laboratory at the University of Michigan for testing with a handheld Raman spectrometer, the TruScan^{TM} RM. Testing consists of comparing a purchased tablet with a separate, high-quality authentic tablet of the same brand. As part of testing we collected high-quality tablets from manufacturers and wholesalers in Uganda, and built a "spectral library" for the study. Each purchased tablet was tested at least once according to a strict protocol.[66] Our analysis is restricted to those dosages for which we were able to obtain a comparison high-quality tablet (N=879).[67]

2.4.3 Definitions of Drug Quality

We define "counterfeit" as a purchased dosage ("sample") for which at least one tablet within the sample failed the spectrometry analysis. We aggregate to the transaction/sample level in order to standardize the unit of analysis. Note that the majority of medicines studied are non-branded "generics"; we are not comparing the chemical composition of a generic to an innovator brand, but rather a given brand to itself. "Counterfeit" refers to a tablet that has a different Raman spectrum than the authentic comparison tablet of the labeled brand. However, many brands are chemically similar. In addi-

[66]The protocol is listed in the Online Appendix for the companion paper, Fitzpatrick (2015).

[67]To protect respondent and manufacturer confidentiality, we do not publish quality results by brand or disaggregated results that could potentially identify outlets or locations.

tion, although tablets are intended to have uniform and consistent contents and manufacturing, some brands may have high within-brand variation. In practice a tablet that failed the comparison against its own high quality authentic tablet could potentially match against another brand within the library.[68] We define "substandard" as a subset of counterfeit medicines where the tablet's spectra could not be matched to any high-quality authentic in the library. 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.

One potential concern with our methodology is that the high fluorescence of the artemether can affect the validity of testing with the handheld spectrometer. Hajjou et al. (2013) and Bate and Hess (2010) perform validation exercises on a previous version of the TruScan^{TM} RM. Both studies confirm that there are a relatively high number of false-positives with respect to AL, implying the potential bias from our method of testing would likely lead to an *overestimate* of the rate of counterfeit and/or substandard drugs.[69] Since the bias of the test is of a known direction, we retest all failing tablets and a random subset of dosages with all passing tablets. This subset is 11 percent of all purchased tablets (N=2322). Results are in Appendix Table

[68]This is known as "low selectivity", because many drug compositions are similar. Among high-quality tablets of AL, for example, all brands were identical enough to at least one other brand to pass. The selectivity tests are asymmetric and non-transitive, because Brand A can be similar to Brand B, and Brand B can be similar to Brand C, but Brand A can be different from Brand C.

[69]We are conducting additional analysis in order to estimate precisely the rates of Type I and Type II error with the updated version of the machine that was used.

2A.1. Conditional on a tablet passing the first scan, the likelihood it passes the second scan is 98 percent; conditional on a tablet failing the first scan, the likelihood that it fails the second scan is 75 percent. The correlation of results across scans of the same tablet is 0.6659.

By aggregating the tablet results to the transaction level, we are able to reduce the amount of variability in results. Conditional on a sample passing according to the first scan, the likelihood that the sample would maintain its classification in the second scan is 100 percent. Conditional on a sample failing according to the first scan, the likelihood that the sample still fails under subsequent testing is 72 percent. Therefore, by using a conservative estimate of whether the tablet failed all of its scans, we are able to reduce the spectrometer bias towards counterfeit medicines. We conclude that our testing methodology is valid and internally consistent. In terms of external validity, however, our results may represent an upper bound on the rate of low-quality antimalarial drugs.

2.4.4 Other Data Sources

Later, we revisited the same outlets and conducted an extensive survey on their background and shop operations (N=452). These surveys include 424 outlets where at least one dosage was purchased, and 415 outlets with a complete survey and a purchase that was also part of the analysis sample (77 percent of all establishments). Enumerators recorded their observations of the shop establishment, a facility observation survey. Among all purchases,

we estimate that 85 percent of the individuals who dispensed the medicine also answered the survey.[70] In addition, surveys with real customers were conducted at the same outlets (N=867). Of all of these customers, 372 had purchased an antimalarial drug. All quality data and data at the transaction come from mystery shopper purchases; no purchases from real customers were tested. There is no correlation between drug quality and survey completion, or drug quality and whether or not real customers were interviewed at the store (not shown).

2.5 Descriptive Results

Before summarizing our key results on quality, we first present summaries of outlet characteristics, including vendor beliefs on fake drugs. We specifically frame our discussion in terms of the vendor and institutional characteristics that may affect the prevalence of low quality, and that we will later use as correlates in our empirical analysis. We then present our key result that drug quality is high in the study area, and that low-quality drugs are typically diluted versions of high-quality drugs.

[70]Following both mystery shopping and the vendor survey, a member of the study team filled out a short survey with a physical description of the dispenser or respondent. We then take the difference in observations, controlling for study team member fixed effects, and estimate a probit regression where the left hand side is instances where we are sure there is or is not a match. We then use as a cutoff for a match 0.50 of the predicted values.

2.5.1 Averages from Vendor Data

We summarize responses from the vendor survey in Table 2.1.[71] Most vendors are women; only 23 percent are men. The average outlet has 2.32 employees. Although we purposely did not ask about whether the outlet was formal or informal, we estimate that only 36 percent of vendors meet the legal qualifications to dispense medicines. Similarly, regulation in the operating environment is not universal: 69 of drug shops report that their outlet had been visited by a representative of the NDA, the regulator of drug shops.[72] Outlets are somewhat profitable and have access to credit. Twenty-two percent of outlets report currently having any debt or loan obligations, including through informal networks.

Despite the lack of formal qualifications, vendors are important sources of healthcare for their communities. On average vendors treat 21.8 customers per day (median value: 15), of which 6 are treated for malaria. Vendors generally are aware of proper medical protocols for malaria. Eighty-four percent of respondents to the survey correctly report AL as the first-line treatment, and eight-one percent generally knew the correct protocol for taking AL. However, the advice given to mystery shoppers is, on average, slightly worse than responses given to enumerators during the survey. Among vendors making a drug recommendation, 75 percent recommended AL and 11 per-

[71] A summary of real shopper data is in Appendix Table 2A.2, and a summary of mystery shopper characteristics is in Appendix Table 2A.3.

[72] Fifty-three percent of the outlets are drug shops; 40 percent are clinics; the remainder are primarily pharmacies.

cent recommended another first-line treatment. In 9 percent of transactions, the vendor recommended SP, which is no longer an effective medicine. The distribution of recommendations is approximately the same at outlets where the respondent correctly reported the first-line treatment, indicating a gap between knowledge and practice.

There is a similar gap between practice and optimal public health practices. Despite the risks of increased drug resistance if individuals sick with malaria taking partial dosages, vendors frequently sell partial dosages. Vendors report only 66 percent of customers buy a full dose, potentially reflecting the expense of first-line treatment. This relatively low fraction may also make it easier to dilute medicines with substandard tablets, as it provides a way for vendors to justify mixing packs. Similarly, despite the need to clinically diagnose malaria with a blood test (either rapid diagnostic testing, or RDT), only 53 percent of establishments offer testing services. Even conditional on having tests available, only 44 percent of mystery shoppers were advised to have the patient take a malaria test.

On the drug vendor survey, we included a module on counterfeit and low-quality drugs. We first asked vendors why other vendors would sell a fake drug. Of those answering the question, 85 percent suggested the reason was related to money, or increasing their profits; only 15 percent thought it was ignorance, and that vendors couldn't identify fake drugs in their stores. We then asked vendors what percentage of outlets in their parish and their district sold fake drugs. On average, vendors thought that 32 percent of

outlets in their parish sold fake drugs; and 44 percent of outlets in their district sold fake drugs. Thirty-eight percent of respondents thought that they could identify a fake drug if they saw one.

We also asked vendors about their thoughts on what the social sanctions would be if a vendor was to be caught selling low quality drugs. Only 6 percent of vendors thought that there would be no consequences to selling a low quality drug. Nearly all respondents (95 percent) believed that the vendor would be reported to authorities, and 93 percent thought that customers would boycott their store. Ninety-two percent thought that the shop would be closed, and 88 percent believed that the stock would be confiscated. Seventy-seven percent of vendors thought that customers would do something violent (vigilante justice).

2.5.2 How available is AL? Results from Covert Shopping Data

We find that stock-outs are relatively rare and that AL was readily available in most of the study area. In Table 2.2, we show that shoppers were able to purchase AL during 86 percent of the 933 successful purchases (N=806). This average translates into a purchase of AL at 92 percent of drug outlets. While smaller fractions of the sample, quinine and SP are also commonly available and purchased drugs. It is important to note that there are different characteristics associated with the different active ingredients. For example,

quinine is highly likely to be sold as an incorrect dosage. These differences may originate due to standard packaging. While AL is typically sold in blister packs– allowing customers to recognize a full dosage more easily– quinine is typically sold as loose tablets in bulk-size bottles. The fact that quinine is often dispensed as loose tablets may make diverting this type of drug from the public sector easier. While 7.8 percent of the AL sample and 8.9 percent of the AL had public sector markings, 17.6 percent of the quinine sample had public sector markings.

While AL is typically available, it is relatively expensive compared to the other treatments. The high price may deter utilization, although discounts are available for those who can bargain. The average price of AL is $3.19, compared to $2.48 for quinine and $1.12 for SP. There is also a substantial amount of variation in prices, for each active ingredient. As measured by the coefficient of variation, prices vary substantially for each type of active ingredient, from 0.39 - 0.46.[73] Note that the type of drug purchased was decided through our study protocol. Therefore, we do not use the type of active ingredient as an outcome variable in our analysis.

2.5.3 Low Quality Drugs or Diluted High Quality Drugs

Overall, we find that drug quality is relatively high in the study areas compared to previous studies, and that low-quality drugs are characterized by

[73]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.

dilution of high-quality drugs. We find that average rate of counterfeit drugs across all transactions is 17 percent, but the average rate of low-quality drugs across all transactions is 3.4 percent. However, the average rate of outlets ever selling a low quality drugs across is slightly higher. We find that counterfeit drugs were sold at 25 percent of outlets, and substandard drugs were sold at 5.6 percent of outlets.[74]

One caveat to interpreting these averages, and the subsequent results on correlates, is that we are only able to test drugs that are part of the analysis sample. Because the focus of the study is AL, AL is more likely to be part of the analysis sample. Thus, we were able to obtain a high-quality tablet for 99 percent of the AL sample. In contrast, only 53 percent of the quinine sample is also in the analysis sample and 81 percent of SP is also in the analysis sample.[75] Conditional on being in the analysis sample, we find substantial differences in terms of drug quality rates by active ingredients. In fact, SP and "other" antimalarials are never found in our sample to be either counterfeited or substandard. The substandard rate for quinine is particularly high, at 47.2 percent.

The difference between the average rates at the transaction level and at the outlet level indicate that outlets tend to sell both high and low quality drugs. Similarly, tablets within a dosage are typically a mixture of both high

[74]Note that if only one mystery shopper purchase had been made per store, the percentage of outlets selling low quality drugs would have decreased.

[75]Because quinine is often sold as loose tablets, we could not always identify the appropriate brand for testing.

and low quality. Within the group of samples with at least one counterfeit tablet, on average 61 percent of tablets were determined counterfeit; within the group of samples with at least one substandard tablet, on average 47 percent of tablets were substandard. We interpret this quality dilution as a strategic response to avoid detection. This interpretation is reminiscent of Salop (1977)'s seminal work on price variation: by increasing noise in the distribution of prices, providers make it difficult for consumers to distinguish high-priced sellers from low-priced sellers. We conclude that by selling both high and low quality, vendors introduce noise in the process, making it more difficult for consumers to learn about true drug quality.

2.5.4 Geographic Distribution

The average rates, however, masks substantial heterogeneity within Uganda. Figure 2.6 presents bar charts of how the average counterfeit and substandard rates substantially vary by district, by as much as 50 percent. In Figure 2.7 we display graphically in a bar chart for each of the 44 parishes the average counterfeit and substandard rate. A counterfeit drug was sold in 46 percent of villages, and in 59 percent of parishes. These figures demonstrate that previous studies based upon an average rate within a country may not be appropriately capturing the variation within a country. Likewise, studies that aggregate averages from a large number of countries may therefore be masking important variation in the average rate of a given country.

In our study, we find that population density predicts drug quality. We

find that urban areas have higher rates of counterfeit drugs, but rural areas have slightly higher rates of substandard medicines. In particular, 13.2 percent of transactions in rural areas were counterfeit, and 5 percent were substandard. In contrast in urban areas, 18 percent of transactions were counterfeit, but only 3 percent were substandard. Similarly, at the outlet level, 20 percent of rural outlets sold a counterfeit drug, and 7 percent of outlets sold a substandard drug. In urban areas 26 percent sold a counterfeit drug and 5 percent of outlets sold a substandard drug.

2.5.5 Comparison to Previous Studies

One challenge with comparing our results to the previous literature is that the bulk of existing studies have small samples or non-random sample selection criteria. For example, in the meta-analysis by Nayyar et al. (2012), only 5 studies with data from African countries collected data on artemether-lumefantrine, and all use convenience sampling. The average of those studies indicate a substandard rate of approximately 30 percent. When considering other types of antimalarial drugs, the view is similar. Only six of the twenty-eight studies cited in the meta-analysis rely on random sampling methods, and only three of those studies based on random sampling have more than 50 observations. More recent work by Kaur et al. (2015) formalizes this intuition with a study in Nigeria. The authors find that convenience sampling yields a substantially higher rate of low-quality drugs than random sampling. The authors also find that there is little difference in the drug quality rates

between mystery shopper and overt shopper purchases, where providers gave informed consent to have their drugs tested for quality.

An additional difficulty is that the methodology for testing differs substantially from study to study, and using equivalent definitions across different testing methodologies is not always possible. For example, Bjorkman et al. (2012) use an older version of the handheld spectrometer which allow for a measure of the counterfeit drug rate; they estimate that 21 percent of drugs in select areas of Uganda are counterfeit. However, the updated version of the machine that we use allows for repeat testing on the same tablet, allowing us to cross-reference failing tablets to further estimate if they are medically effective ("substandard"). Our results imply that substandard drugs are substantially less common at 4 percent.

We cannot conclude, however, that Bjorkman et al. (2012) would have also found a low prevalence of substandard drugs had they done additional testing for two main reasons. First, in 2012, after the data of Bjorkman et al. (2012) was collected and before this study took place, the National Drug Authority closed a national manufacturer of substandard antimalarial drugs. This event was highly publicized throughout the country (Mugisa, 2012). Closing down a low-quality manufacturer would have a direct effect of eliminating a primary source of low-quality medicines, and an indirect effect of causing competing firms to increase quality to avoid closure. Secondly, the sampling methods between our studies differ substantially and have little overlap. Bjorkman et al. (2012) used drug outlets located in project villages

in exclusively rural areas, and 55 percent were monopolists. Our results are based upon random sampling methods from both urban and rural areas, and only 6 percent of vendors are monopolists.

In conclusion, the average findings reported in previous literature are potentially upper bounds on the true drug quality rate. However, due to the nature of the testing methodology, definitions used, sampling strategy, and other ongoing events in the market, it is potentially misleading to make comparisons to any previous study specifically. However, by our estimation, the rate of ineffective medicines is less than 4 percent in the study area, suggesting that low quality drugs are not widespread in all areas of developing countries.

2.6 Empirical Analysis on Correlates

In our empirical analysis, we first test what transaction-level correlates are associated with drug quality. Second, we analyze the outlet-level correlates of low quality drugs. Whether the drug quality rate for outlet i (transaction i) is correlated with a given characteristic X is analyzed through the following regression:

$$Quality_{ip} = \beta_0 + \beta_1 X_i + \gamma_p + \mu_{ip} \tag{2.10}$$

where *Quality* is measured in two primary ways: whether or not at least one tablet within the dosage is substandard, and whether or not at least one

tablet within the dosage is counterfeit. X is a vector of characteristics that are potentially linked with drug quality. Our outcome variables of drug quality are binary, and we use a linear probability model to estimate marginal effects. Because there is substantial variation across and within districts, we include a parish fixed effect, γ, to account for any parish-specific characteristics. The fixed effect typically boosts statistical power, although in relevant regressions we show a district fixed effect specification that has more degrees of freedom. We use standard errors clustered at the outlet level to account for any correlations within different purchases of a shop when the unit of observation is a transaction. We use robust standard errors for regressions in which the unit of observation is the outlet.[76]

2.7 Results: Correlates of Low Quality Drugs

2.7.1 Price and other Demand-Side Explanations

We begin by testing the correlation between quality and characteristics of a given transaction that would be observable to customers. These characteristics include price, the number of separate blister packs, whether the dosage had public sector markings ("diverted"), and whether there was an expiration date marked. Results are in Table 2.3.

We find that while counterfeit drugs are priced \$0.01 lower than non-

[76]In order to increase statistical power, we use the full set of non-missing observations available for each group of outcomes. As a result, the sample size may differ between regressions using the same data.

counterfeit drugs, there is no correlation between price and whether the drug is substandard. Assuming patients care primarily about the efficacy of drugs, the lack of a price discount for low quality is consistent with consumer deception. In contrast, other characteristics of the transaction are potentially stronger, albeit noisy signals. For example, the number of blister packs– loosely thought of as "chances" to dilute the dosage – is negatively and strongly correlated with both counterfeit and substandard drugs.[77] Each additional blister pack in the purchase is associated with a 3.3 percentage point higher likelihood of being sold a counterfeit drug and a 2.8 percentage point higher likelihood of being sold a substandard drug. Contrary to expectations, drugs lacking an expiration date are 12 percentage points *less* likely to be counterfeit; there is no relationship between having an expiration date and whether the drug is substandard. Diverted medicines are 26.6 percentage points more likely to be counterfeit and diverted drugs are 9.3 percentage points more likely to be substandard. Particularly for diverted medicines, the sign of the correlation is surprising because medicines in the public sector are quality assured through the Global Fund pre-qualification program for manufacturers. There are two alternative interpretations of the negative correlation of public sector markings with drug quality. One interpretation is that there is corruption and a lack of appropriate control measures as part of the pre-qualification program. Alternatively, adept counterfeiters strate-

[77]Loose tablets were each considered a separate "blister pack" to have the same interpretation.

gically try to make substandard medicines look like public sector drugs. Our data do not allow us to distinguish between these potential explanations.

However, different types of drugs have different dosages, different packaging, and are purchased by different types of consumers. For example, quinine is commonly sold in the form of loose tablets, and SP has a much lower average price than first-line therapies; each of these active ingredients have different chemical quality rates. In columns 3 and 4, we show that whether the drug is diverted and the price are still robust correlates of counterfeit drugs. Similarly, the correlations of substandard drugs are the same when controlling for a drug fixed effect. Each additional blister pack is associated with an increase in the substandard rate by 2.8 percentage points, and diverted drugs are 9 percentage points more likely to be substandard. Results are robust to controlling for mystery shopper fixed effects in columns 5 and 6, indicating that shopper characteristics are not mediating factors in these relationships.

We now turn to identifying whether vendor behavior during the transaction is associated with drug quality. We consider two sets of independent variables, objective and subjective characteristics. Results are presented in Table 2.4. There are few robust characteristics of vendor behavior and drug quality. Among the group of objective characteristics, the only significant correlation is with drug quality and whether the provider asked any questions about the patient, either health-related questions or otherwise. Shoppers who reported that the dispenser asked any questions about the patient

were 9-10 percentage points less likely to dispense a counterfeit drug, and 5-7 percentage points less likely to dispense a substandard drug. In addition, dispensers who were rated as "very unfriendly" were 8-10 percentage points less likely to sell a counterfeit drug, and 2-3 percentage points less likely to sell a substandard. These correlations are robust to mystery shopper and drug type fixed effects.

Customer Correlates/Discrimination- Mystery shopper data

We next turn to examining whether certain groups of customers are more likely to receive low-quality drugs, as in either taste-based or statistical discrimination. We begin by examining characteristics of the shoppers that purchased the drug during mystery shopping. Results in Panel A of Table 2.5 show that female shoppers are slightly less likely to buy both counterfeit and substandard drugs, although p-values are outside the range of statistical significance (p-value in Column 4 = 0.15). Similarly, shoppers that were of a minority tribe in that district are slightly more likely to buy counterfeit but slightly less likely to buy a substandard drug, although p-values are outside the range of statistical significance (p-value in Column 4 = 0.179). Both gender and being part of a minority tribe are significant in simple regressions with parish or district fixed effects, without controlling for the other, suggesting that there might be an issue of statistical power due to multicollinearity. There are only 16 different shoppers.

In Panel B, we examine whether the vendor's response to the tribe or

gender of the shopper depend upon the gender or tribe of the vendor. This analysis slightly restricts our sample size because we condition on the person who dispensed the medicine being the person who answered the survey (N=603). We find that shoppers of the same tribe as the vendor are 8.5 percentage points *more* likely to be sold a counterfeit drug and 4 percentage points more likely to be sold substandard drug, although point estimates are different from zero only when controlling for a district fixed effect. Being of the same sex as the vendor is unrelated to quality.

The finding that female mystery shoppers receive a higher quality may be consistent with taste or statistical discrimination in favor of women. However, there is certainly gender inequality in Uganda, and women have lower incomes, less education, and lower bargaining power within the household. Similarly, both male and female vendors react similarly to gender of the mystery shopper. In Appendix Table 2A.4 we show that instead this observation may reflect other demand characteristics correlated with gender. Women are culturally in charge of healthcare and may be more likely to be "regular" customers. Women are also given a higher offer price, more likely to successfully bargain, pay the same prices on average, and are less likely to be offered additional products for the treatment of febrile symptoms. They are given the same service quality on average; members of a minority tribe are given higher service quality.

Time of Day/Day of Week

A more subtle characteristic associated with consumer demand characteristics may be when customers tend to shop. For example, anecdotal evidence suggests that farmers tend to go to trading centers during the day, when it is too hot to work, or after dark. Thus, we test whether the time or day a shopper visited an outlet changes the quality of the resulting sale. Results are in Table 2.6. Although there is no linkage between time of day and drug quality, substandard drugs are 3.9 percentage points less likely to be sold over the weekend than during the week. These results are robust to controlling for drug type and mystery shopper fixed effects. Prices are also $0.18 higher on weekends than weekdays (not shown). Systematic quality fluctuations may indicate that certain types of customers shop different days of the week, and that vendors respond to these demand fluctuations.

Real Customer Characteristics

Finally, we can also examine whether characteristics of real customers are correlated with drug quality. Results are in Table 2.7. To account for differential response by shop, we average responses to the survey of real customers at the outlet level. Excluding missing values, we are left with relatively few observations, 277. Though we caution that we have limited statistical power, we find that few characteristics of real customers at the outlet are correlated

with drug quality.[78] We use customer's malaria test score, the average number of correct responses of six questions as a proxy for health literacy. We use the average likelihood that the customer had shopped there before as a proxy for whether mystery shoppers may have stood out more. We use other measures of demographics– log income, distance walking to outlet, gender, and whether the patient was buying for an adult patient. We find that the average percentage of adult patients is correlated with whether the outlet sold a counterfeit drug, and that the percentage of female customers is negatively correlated with whether the outlet sold a substandard drug. This is similar to the correlation observed between the gender of mystery shopper and drug quality.

2.7.2 Supply-Side Explanations

We now change our unit of analysis to be the outlet level, to test if low quality outlets have specific characteristics. There is a large policy emphasis on establishment type, including legal requirements for operation and training of staff and differences in costs of licensing. Therefore, we begin by testing whether establishment type is correlated with drug quality. We find little evidence that establishment type is correlated with drug quality. Results are in Table 2.8. In Columns 1 and 2, we use the full sample of all outlets with

[78]The reader should potentially also interpret results with additional caution. Recall that drug quality is from a separate dataset, the transaction data from covert shoppers. Thus standard errors may be upward biased for not accounting for the different sampling errors.

purchases; in Columns 3 and 4 we replicate the analysis with the sample of all purchases at which a survey was also completed (excluding missing values) in order to look at additional outlet characteristics. Although establishment type is not related with quality, establishment type is strongly correlated with the price paid. Compared to pharmacies, clinics charge on average \$0.72 higher and drug shops charge \$0.36 higher per dosage. These results are robust to using the mystery-shopper establishment classification and also the self-reported establishment type on the vendor survey.[79] Moreover, the lack of observed quality differences with respect to establishment type is not simply semantic. Compared to pharmacies, clinics are 41 percentage points less likely to have a qualified person working there; drug shops are 45 percentage points less likely. However, clinics and drug shops are more likely to have a license on display in view of the enumerator. Pharmacies also have a substantially larger selection of antimalarial drugs, nearly 7 more antimalarial drug options than clinics or drug shops. Although establishment type does signal to customers specific characteristics of the outlet, establishment type does not help customers distinguish high quality drugs from low quality drugs.

Although the simple establishment type classification is not descriptive, some more specific characteristics related to the physical appearance of the store may be related to drug quality. We next test whether various facility

[79]Price and quality are also not related to whether the mystery shopper classification was the same as the self-reported establishment classification.

characteristics that might make drugs more likely to degrade over time are related to the counterfeit rate. We find that substandard medicines are not consistent with poor storage conditions. Many coefficients are not different from zero. Those that are significant go in the "wrong" direction: there is actually a positive relationship between drug quality and some measures of poor storage conditions. Results are in Table 2.9. Outlets which were observed to either have a manual recording system or no system at all ("low technology") are 31 percentage points more likely to sell counterfeit drugs, although 7.8 percentage points less likely to sell substandard drugs compared to outlets which kept records electronically. A store that was classified as "very crowded" is 5.2 percentage points less likely to sell a substandard drug, although no more likely to sell a counterfeit drug. Stores with a concrete floor (as opposed to a dirt floor) are 16.6 percentage points less likely to sell a counterfeit drug but no more likely to sell a substandard drug. Similarly, inventory on the floor of the establishment is associated with a 13.5 percentage point lower likelihood (insignificantly different from zero) of selling a counterfeit drug and a 6 percentage point lower likelihood of selling a substandard drug. Subjective shop quality was unrelated to measures of quality. Although there may be potential issues of multicollinearity, reported point estimates are approximately the same when characteristics are examined separately in a simple regression; results are also robust to including controls for establishment type. These coefficients are all inconsistent with a story where poor storage conditions indirectly cause low quality drugs.

On the drug vendor survey, we also asked about the typical supply chain processes. Results are in Table 2.10. Although not always significant, there is a suggestive relationship between outlets who buy their drugs from mobile providers/promoters and drug quality. Outlets who purchase from drug promoters are 12.4 percentage points more likely to sell substandard drug (p-value = 0.104). This result is robust to including a drug outlet fixed effect. Furthermore, the lack of statistical significance may reflect a lack of statistical power as opposed to the lack of a relationship. In Columns 5 and 6, we control for a district fixed effect as opposed to a parish fixed effect, freeing up additional degrees of freedom. In the specification with an outlet fixed effect, outlets purchasing from drug hawkers are 11.8 percentage points more likely to sell a substandard drug, significant at the 10 percent level. These results suggest that substandard drugs enter the supply chains through mobile drug hawkers/promoters.

2.7.3 Institutional Factors/Competition

Table 2.11 examines whether other characteristics of the establishment, or the operating environment are correlated with drug quality. Whether the outlet has a name posted outside– a proxy of whether the outlet attempts to avoid regulation– is uncorrelated with drug quality, as is whether the outlet has been inspected by a regulator or government official in the past 6 months. There is some suggestive evidence that less profitable establishments are more likely to sell substandard drugs, but this correlation is not apparent in all

specifications. Similarly, there is suggestive evidence that outlets with debt, and more employees, are more likely to sell counterfeit drugs. Other characteristics, including whether the respondent had ever taken a class on business management, whether the outlet tested for malaria, whether the outlet had beds, or whether the outlet charged a consultation fee, are unrelated to drug quality in all specifications.

Finally, we consider the effect of competition on drug quality. Results in Table 2.12 show that in the cross-section, competition is correlated with higher quality, and the effect of competition differs by the type of outlets in the market. Having a public health facility in the village is associated with a 24 percentage point decrease in the likelihood of an outlet selling a counterfeit drug, but no significant difference in terms of the likelihood of selling a counterfeit drug. Each additional drug shop in the market decreases the likelihood an outlet sells counterfeit drugs by approximately 1.3 percentage points, and decreases the likelihood an outlet sells a substandard drug by 0.6 percentage points. Although the number of clinics is not correlated with quality, there is a significant relationship with pharmacies and whether the outlet sells a substandard drug. Each additional pharmacy decreases the likelihood that an outlet sells a substandard drug by between 3-5.6 percentage points.

Aside from counts of establishments, there are also other ways to measure competition in a market. We also consider the Hirfandahl-Hirshman index (HHI), a standard measure of concentration within a market, as well as the

distance walking to the nearest public or private facility. The HHI is the percentage of sales within the village that are attributed to a given provider, and its highest value is 1 (a monopolist). The HHI is a consistently strong predictor of drug quality, where less competitive areas have higher rates of both counterfeit and substandard drugs. On the other hand, the distance to the closest competing outlet– either public or private– is uncorrelated with quality.

2.8 Discussion

One key institutional detail relevant to the interpretation of results is whether vendors are complicit in the sale of low-quality drugs. If shopkeepers knowingly distribute low-quality drugs, then providing education or training is unlikely to improve market quality. Instead, limited resources should instead be spent on increased monitoring, potentially at drug factories or points of entry. If providers are also being duped by suppliers or are unaware of degrading drug inventory, then raids and shop closures – the current policy approach – may be unfair, expensive to maintain, and limit healthcare access. Similarly, if suppliers are unaware of drug quality, then training programs should be conducted to improve quality. We answer this question in several ways. First, we conduct a list randomization exercise (Kuklinski et al., 1997; Karlan and Zinman, 2012). Next, we examine whether all of the other available evidence suggests vendors know the quality of their work. Finally,

we discuss the key question motivating policymakers concerned about low-quality drug rates: what policies would be the most effective? We answer all of these questions using data from the vendors themselves.

2.8.1 Do Drug Vendors Know Quality?

One way to determine if vendors know the quality of the drugs that they are selling is to simply ask them through direct elicitation. However, direct elicitation may lead to systematic response bias. In addition to admitting to an illegal activity, for which they would be potentially accountable, vendors may also be unwilling to confess to an enumerator their culpability. To overcome these response challenges, we conduct a survey exercise ("list randomization") intended to have individual responses be individually compatible with truth-telling by masking individual responses.

The list randomization exercise works as follows. We randomly divide survey respondents into "Treatment" and "Control" groups. Respondents in the control group are shown a list of activities and asked to report how many of the activities they had done. Respondents in the treatment group are shown the same list of activities, plus one sensitive activity, and asked to report how many activities that they have done. The difference between the two groups identifies the proportion of the sample estimated to have done the sensitive activity, without revealing the behavior of any individual respondent. Thus, it is incentive-compatible for respondents to report truthfully. We implement this methodology on the vendor survey for three

different sensitive activities: paying a bribe to the regulator (the National Drug Authority, or NDA); selling antibiotics when they knew it was unnecessary; knowingly selling a fake drug.[80] The purpose of asking about multiple sensitive activities was to compare against known problems in the market as a check on whether the methodology worked as intended.

We use the following Intention-to-Treat specification to estimate the proportion of the sample that has ever done a particular sensitive activity:

$$NumberActivities_i = \lambda_0 + \lambda_1 Treatment_i + \delta' X + \gamma_d + \epsilon_i \tag{2.11}$$

where $NumberActivities$ is the number of activities from the list that the respondent reported having ever done; $Treatment$ is an indicator variable for whether the respondent was assigned to see a sensitive activity on their list; X is a vector of characteristics to control for potential omitted variables and account for the way the exercise was implemented; γ is a district fixed effect; ϵ is a heteroskedastic error term.[81]

One important assumption behind the list randomization technique is

[80] Note that in terms of the survey module for list randomization, both English and local languages were used. The English word used was "fake", but each of the local languages have the same word for counterfeit/fake/substandard.

[81] There were two different list sheets shown to respondents. The first had the "fake drug" sensitive activity first; the second had it third. In addition, due to concerns about anonymity, the non-sensitive activities shown to each group in the "fake drug" treatment were slightly altered in the second round. While implementing the survey in the field, the enumerators expressed concerns about the relevance of the list of non-sensitive activities, because it also included drinking and visiting Nakumatt, store that was not in all locations. Therefore, we control for the list seen and survey round in all regressions.

that randomization was implemented correctly and resulted in two comparable groups. Preliminary results in Table 2.13 show that there is some degree of imbalance for several characteristics. Specifically, respondents who were male were significantly more likely to be in the treatment group for the "antibiotics" and significantly more likely to be in the control group for the "fake drug" group. Similarly there is also some imbalance in some treatment groups for whether the respondent was the owner of the outlet or distance to the nearest public facility. It is unclear how these differences could have arisen, although some differences may be expected due to chance alone. Regardless, we control for these imbalanced characteristics in our estimation.

Results of the list randomization exercise are in Table 2.14. The results from the "bribe" activity show that 17.2 percent of the sample report having ever paid a bribe to a regulator during an inspection, significant at the 10 percent level. However, results for the "antibiotics" and "fake drugs" lists show that the fraction of the sample admitting to doing these activities knowingly is small. Although not significant from zero, the point estimate suggests that approximately 6.2 percent of the sample has knowingly sold an antibiotic when it was not necessary and 6.7 percent of the sample has knowingly sold a fake drug, The respective 95% confidence intervals are [-14.8, 27.15] and [-10.7, 24.1].

So do vendors know when they sell low-quality drugs? While the list randomization was inconclusive, it should be noted that the estimated proportion of the sample knowingly selling a fake drug is approximately the same

as the empirical average of 5.6 percent of outlets which sold a substandard drug to a mystery shopper. Recent research has suggested that list randomization may have a downward bias due to cognitive difficulties in adding up responses (Su, 2015).

In addition, we can look at the accumulation of evidence in previous research, including this paper and in Fitzpatrick (2015), which shows that vendors strategically allocate drugs to customers who are statistically less likely to return to a given outlet. Of course, if vendors did not know drug quality, then we would still expect some characteristics to be significantly related by chance alone. However, the most likely mechanism associated with this result– drug degradation on shelves– does not hold up empirically. Furthermore, there are suggestive relationships between quality and selling through drug hawkers, as well as the prevalence of diverted medicines (i.e., other illicit behavior). In contrast, observable characteristics that customers could use to easily avoid low quality places– such as establishment type– provide no guidance. In addition, two randomized studies have found competition improves quality– interpreted as a strategic response to increase profits. All together, these facts suggest that at least a subset of vendors know the quality of the drugs they dispense and are complicit in this deceptive practice. This interpretation is also consistent with the figure we report of 85 percent of vendors suggesting that fake drugs are sold in order to increase profits, because they are lower cost inputs.

2.8.2 How to Improve Drug Quality?

We asked what potential policy interventions the vendors themselves thought would be effective at reducing low-quality drug rates. Results are in Table 2.15. From a policy perspective, implementing fines and standardizing jail penalties for being convicted of selling low-quality drugs should have an important deterrence effect. Moreover, there is an ongoing debate over penalties for selling fake drugs among lawmakers in Uganda. For those convicted of selling low-quality drugs, vendors recommended a median fine of 1 million UGX ($386), and the average jail term of nearly 9 years, with a median jail term of 3 years. These penalty recommendations are uncorrelated with quality (not shown).

Respondents were also asked to rank the potential policies on a scale of 1 ("definitely will not work") to 4 ("definitely will work"). The most popular policy intervention that was thought to be most effective was to increase training programs for vendors and/or pharmacists to recognize fake drugs; 97 percent of the sample thought that would be an effective strategy. Overall, 95 percent thought that increased inspections at borders and points of entry would be effective; 91 percent thought that increased inspections at outlets would be effective. Only 87 percent thought that increased fines and 85 percent thought that increased jail sentences would be effective. The relatively least popular policy was consumer education campaigns, although 80 percent of respondents still thought that such a policy would be effective.

2.9 Conclusion

Recent empirical evidence suggests that low quality healthcare is prevalent in many developing countries. One example of the problem of low quality is the problem of fake, or counterfeit antimalarial drugs. Improving the quality of antimalarial drugs is important to encourage appropriate and effective treatment, reduce medical complications, and improve health. In addition, if counterfeit drugs increase drug resistance of malaria, then reducing their prevalence becomes a significant public health concern. However, there is little evidence on the prevalence of low quality medicine in Uganda, and little guidance for policymakers on where to target anti-counterfeit policy with scarce resources.

In this paper, we contribute to the existing literature on low quality drugs. We first estimate the average rate, and are among the few to do so with a a large, representative sample. We find that the rate of counterfeit drugs is approximately 17 percent, but the rate of substandard drugs– those less likely to be medically effective– is approximately 4 percent. Second, we provide important insight into identifying the mechanisms through which low quality drugs infiltrate markets. By combining unique and detailed datasets on both supply and demand characteristics, we provide new empirical analysis on correlates of low-quality drugs. We find measures of regulation are uncorrelated with drug quality rates, potentially reflective of ineffective institutions in resource-poor environments. However, competition may be a

market-based manner in which to improve drug quality. We find that poor storage conditions, and subsequent degradation, are an unlikely cause of substandard medicines. In contrast, mobile hawkers and drug promoters appear to be one way substandard medicines enter the supply chain.

We find that customers would have a difficult time discerning low-quality drugs on the basis of price or characteristics of the vendor. Vendor behavior changes only slightly when they are selling a low-quality drug. We find low-quality drugs are typically dilutions of high-quality dosages. It is relatively uncommon for vendors to sell a complete dosage of ineffective tablets. In dosages with substandard drugs, on average only half of tablets fail a handheld spectrometer test. We interpret this dilution as strategic behavior: dilution increases noise, and makes it more difficult for customers to learn about true drug quality from personal experience. We find that men are more likely to be sold substandard medicines.

Our final result is that a small percentage of vendors are complicit in the sale of low-quality drugs. The point estimate on knowingly selling a fake drug is similar to the empirical average, although not significant. In addition, other circumstantial evidence–such as responses from the vendors themselves on why an outlet would sell low-quality drugs– and results from previous literature make it harder to justify that these correlations and causal effects come about without any knowledge of the provider.

The relatively high rates of drug quality we observe are contrary to recent research based upon small samples and nonrandomized. Ex-ante, it is un-

clear whether the existing literature represents an upper or lower bound on low-quality drug rates. For example, in rural areas, vendors may personally know their clients and similarly the lack of competition may make reputation motives to sell high-quality drugs very salient. On the other hand, in urban areas, regulation may be higher, and the larger number of people may mask accountability. Our data indicate that although the rate may differ substantially between different geographic areas of the same country, previous work is likely an overestimate of the rate of low-quality drugs.

We fully acknowledge that drug quality rates could be different in different study areas, or among different drug classifications. In the study area, malaria represents the number one burden of illness; results may in particular differ in areas where malaria is less common, or where the local population is less familiar with this illness. Regardless, the fact that our overall results indicate that substandard and counterfeit drugs are substantially less of a problem than previously estimated has important policy implications. We do not conclude that a 4 percent rate of essential medicines as medically ineffective as an "acceptable" rate of drug quality. However, policymakers must make decisions regarding scarce resources based upon the competing needs of their communities. Our results should help them evaluate where to devote money, manpower, and expertise, in order to maximize their impact among their communities, whether it is to further reduce drug quality rates or instead to focus on other problems of healthcare quality. Our results also highlight that future research on drug quality should incorporate technology

and random sampling methods to maximize accuracy, impact, and relevance to the local population.

Figure 2.6: Quality Results by District

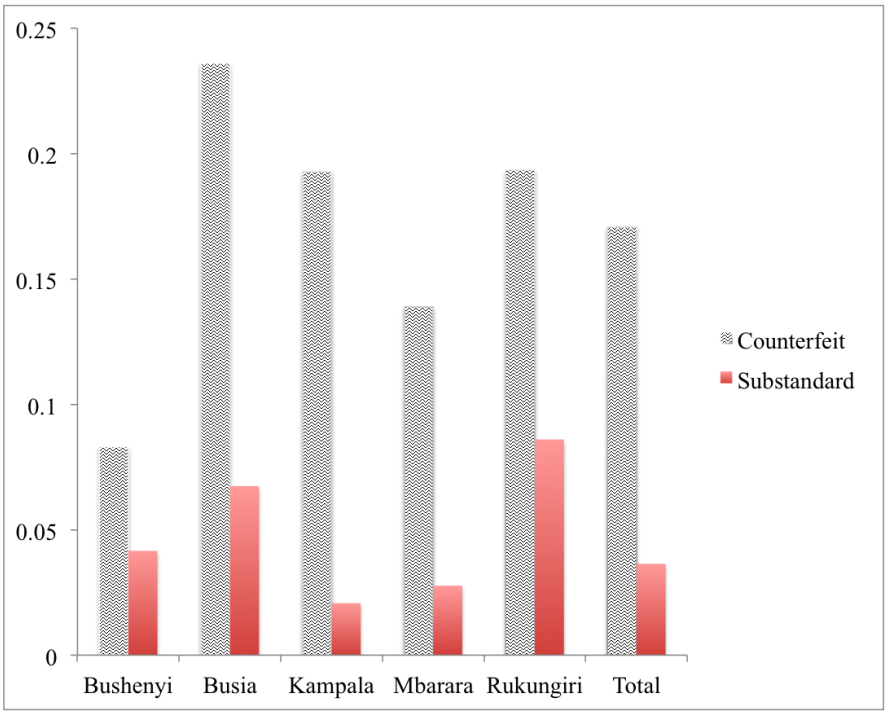


Figure 2.7: Quality Result Averages by Parish

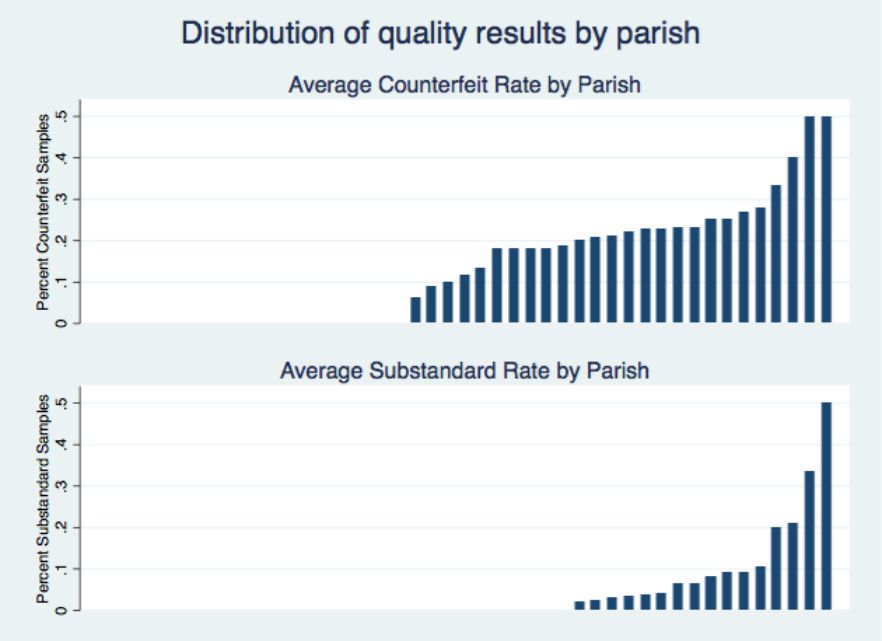


Table 2.1: Vendor Data Summary

Panel A: Vendor Characteristics	
Male	0.23
Number of employees	2.32
Qualified Person	0.36
Visited by NDA in past 6 months	0.69
Any debt	0.22
Number of customers, previous day	21.80
Knows first-line treatment	0.84
Percentage of customers who buy full dose	0.66
Sell malaria tests	0.53
Panel B: Why would a vendor sell a fake drug	
Money or Profits	0.85
Ignorance	0.15
Panel C: Beliefs on fake drugs	
Percent outlets fake drugs in parish	0.32
Percent outlets fake drugs in district	0.44
Could identify fake drugs by sight	0.38
Panel D: Customer reaction to selling fake drugs	
Nothing would happen	0.06
Reported to authorities	0.95
Customers would boycott	0.93
Shop would be closed	0.92
Stock would be confiscated	0.88
Customers would do something violent	0.77

Notes: Data are taken from the vendor survey (N=452). Qualified person is a generated variable based upon responses of education level received by the respondent and the type of establishment, based upon the official regulations. Responses in Panel B are categorized responses to an open-ended question. Percent fake drugs in parish/district are the respondent's beliefs of the percent of outlets selling a fake drug, asked as a number out of 10. Recommended fine is the respondent's recommendation of penalty for those caught selling fake drugs. Recommended jail sentence is the respondent's recommended jail sentence for those caught selling fake drugs, where responses of "for life" are top-coded at 99. Could identify fake drugs by sight is a dummy variable of the respondent's answer to whether they thought they could identify a fake drug if they saw it, excluding responses of "don't know". Responses tallied in Panel D are not mutually exclusive.

Table 2.2: Covert Shopper Data Summary

Variables	AL (1)	Quinine (2)	SP (3)	Other (4)
Number	806	34	79	14
Number of Different Brands	7	5	5	5
Correct Dosage	0.945	0.265	0.949	0.556
Number Blister Packs	1.393	8.706	1.278	2.143
Diverted Drug	0.078	0.176	0.089	0.071
Average Price Paid	3.19	2.48	1.12	3.24
Bargained	0.600	0.529	0.506	0.571
Coefficient of Variation of Price Paid	0.458	0.398	0.452	0.651
Analysis Sample	0.988	0.529	0.810	0.071
Counterfeit	0.186	0.111	0.000	0.000
Fraction Tablets Counterfeit	0.611	0.544	0.000	0.000
Substandard	0.038	0.472	0.000	0.000
Fraction Tablets Substandard	0.468	0.417	0.000	0.000

Notes: Above is a summary of all data collected by mystery shoppers. 'AL' refers to artemether-lumefantrine. 'Quinine' refers to quinine sulphate. 'SP' refers to sulphadoxine-pyrimethamine. 'Other' is all other brands and active ingredients, including those whose active ingredients could not be identified. Number of different brands excludes where the brand was unknown. The correct dosages is based upon the full adult dosage. Number blister packs includes any loose tablets sold as their own pack. Average price paid is in US dollars. The exchange rate at the time of data collection was \$1US = 2593 UGX. Bargained refers to whether the covert shopper was successfully able to reduce the price through bargaining. Diverted drug means a drug with government markings. Analysis Sample indicates that the drug was able to be part of the analysis sample, and able to be tested. This required obtaining an authentic sample of the brand. Counterfeit refers to whether at least one tablet within the dosage failed the handheld spectrometry test and is estimated in the analysis sample. Substandard refers to whether at least one tablet within the dosage failed the handheld spectrometry test and could not be found to match another brand in the library. Substandard is only estimated in the analysis sample. Both fraction of tablets variables are conditional on being counterfeit or substandard, respectively.

Table 2.3: Transaction Correlates

Variables	Counterfeit (1)	Substandard (2)	Counterfeit (3)	Substandard (4)	Counterfeit (5)	Substandard (6)
Number of Blister Packs	0.032*	0.028*	0.036	0.028*	0.034	0.028*
	(0.019)	(0.014)	(0.022)	(0.015)	(0.022)	(0.015)
No expiration date	−0.118**	−0.009	−0.044	0.01	−0.049	0.003
	(0.047)	(0.030)	(0.053)	(0.034)	(0.053)	(0.037)
Diverted Drug	0.266***	0.093*	0.248***	0.090*	0.220***	0.086*
	(0.071)	(0.049)	(0.071)	(0.049)	(0.070)	(0.048)
Price Paid USD	−0.014**	−0.002	−0.023***	−0.004	−0.024***	−0.004
	(0.006)	(0.004)	(0.009)	(0.004)	(0.008)	(0.004)
Constant	0.154***	−0.005	0.191***	0.004	0.144***	−0.039
	(0.032)	(0.017)	(0.038)	(0.017)	(0.053)	(0.028)
Drug Type Fixed Effects			X	X	X	X
Mystery Shopper Fixed Effects					X	X
Observations	879	879	879	879	879	879
R-squared	0.093	0.14	0.104	0.141	0.129	0.156

Notes: Sample is all purchases that could be tested for quality that had non-missing values for all variables. Robust standard errors in parentheses. Above are OLS estimates from a linear probability model. "Counterfeit" refers to a purchased dosage in which at least one tablet failed the handheld spectrometry test; "Substandard" refers to a purchased dosage in which at at least one tablet failed the handheld spectrometry test and also did not match any other brands within the library. The outcome variable in odd columns is whether or not at least one tablet within the dosage was counterfeit; the outcome variable in even columns is whether or not at least one tablet within the dosage was substandard. Number of blister packs is the number of separate packages containing tablets; loose tablets are counted as their own pack. No expiration date is a dummy variable indicating whether or not an expiration date was visible on the package. Diverted drug means that the drug had public sector markets. Price paid is the final transaction price, and is in US dollars. The exchange rate used is \$1US = 2593 UGX. Drug type fixed effect is a set of dummy variables for the drug's active ingredient classification. All regressions control for a parish fixed effect. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.4: Vendor Behavior and Subjective Impressions

Variables	Counterfeit (1)	Substandard (2)	Counterfeit (3)	Substandard (4)	Counterfeit (5)	Substandard (6)
Bargained	0.033	−0.013	0.037	−0.01	0.016	−0.012
	(0.028)	(0.015)	(0.028)	(0.015)	(0.032)	(0.017)
Gave correct instructions	0.041	0.009	0.033	0.003	0.026	−0.001
	(0.029)	(0.012)	(0.030)	(0.013)	(0.034)	(0.012)
Express doubts	0.015	−0.003	0.011	−0.005	0.021	0.006
	(0.034)	(0.012)	(0.033)	(0.013)	(0.036)	(0.015)
Ask any questions	−0.095**	−0.049*	−0.103**	−0.058**	−0.094**	−0.068**
	(0.047)	(0.027)	(0.046)	(0.028)	(0.048)	(0.028)
Picked from back	0.062	0.023	0.052	0.024	0.031	0.018
	(0.052)	(0.027)	(0.052)	(0.027)	(0.052)	(0.027)
Very attractive			−0.053	−0.023	−0.042	−0.02
			(0.071)	(0.033)	(0.070)	(0.034)
Very clear			0.004	−0.011	−0.028	−0.031
			(0.067)	(0.038)	(0.069)	(0.041)
Very confident			0.066	0.043	0.052	0.024
			(0.065)	(0.048)	(0.068)	(0.049)
Very knowledgeable			0.009	0.014	0.002	0.01
			(0.034)	(0.015)	(0.037)	(0.019)
Very friendly			0.046	−0.011	0.035	−0.01
			(0.068)	(0.035)	(0.067)	(0.037)
Very unfriendly			−0.103***	−0.024	−0.088**	−0.032*
			(0.036)	(0.016)	(0.040)	(0.018)
Constant	0.197***	0.079***	0.236*	0.079**	0.215*	0.046
	(0.048)	(0.028)	(0.125)	(0.035)	(0.125)	(0.038)
Mystery Shopper Fixed Effects					X	X
Drug Type Fixed Effects					X	X
Observations	879	879	879	879	879	879
R-squared	0.064	0.103	0.079	0.111	0.113	0.135

Notes: Coefficient estimates are marginal effects from a linear probability model, controlling for a parish fixed effect. Sample is all purchases of antimalarial drugs that could accurately be tested for quality, and data are from the mystery shopper transaction survey. "Successfully bargained" refers to whether the shopper successfully negotiated a price discount. Drug picked from back of outlet refers to whether the vendor went to the back of the outlet, or otherwise left the sight of the shopper, to pick the medicine. Gave correct instructions is a zero If a vendor did not give instructions. There are 29 observations with missing values (including "don't know") for one of the above variables. Missing values were assigned to be zeroes, and a dummy variable included marking the imputation. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.5: Mystery Shopper Characteristics

	Parish Fixed Effect		District Fixed Effect	
	Counterfeit	Substandard	Counterfeit	Substandard
Panel A: Full Sample	(1)	(2)	(3)	(4)
Female Shopper	−0.045	−0.017	−0.045	−0.019
	(0.028)	(0.014)	(0.028)	(0.013)
Minority Tribe	0.027	−0.028	0.027	−0.02
	(0.039)	(0.017)	(0.039)	(0.015)
Constant	0.182***	0.060***	0.182***	0.058***
	(0.026)	(0.014)	(0.026)	(0.014)
Observations	879	879	879	879
R-squared	0.054	0.098	0.054	0.019
Panel B: Matched Sample	(1)	(2)	(3)	(4)
Same Tribe	0.064	0.039	0.085*	0.040*
	(0.048)	(0.026)	(0.044)	(0.024)
Same Sex	0.006	−0.007	0.006	−0.014
	(0.032)	(0.016)	(0.030)	(0.015)
Constant	0.149***	0.033**	0.145***	0.037***
	(0.026)	(0.013)	(0.025)	(0.013)
Observations	603	603	603	603
R-squared	0.076	0.15	0.023	0.024

Notes: Coefficient estimates are marginal effects from a linear probability model. The first two columns control for a parish fixed effect, and the second two columns control for a district fixed effect. Panel A uses all purchases that could be tested for quality and Panel B uses purchases from outlets where the dispenser is the same person who completed the survey. Same Tribe and Minority Tribe refer to the tribe of the shopper. Minority tribe is specific to each district's most prevalent ethnic group. Same sex indicates that the gender of vendor is the same as the gender of the vendor. Counterfeit refers to a purchased dosage in which at least one tablet failed the handheld spectrometry test; Substandard refers to a purchased dosage in which at at least one tablet failed the handheld spectrometry test and also did not match any other brands within the library. Robust standard errors in parentheses,clustered at the outlet level.$***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.6: Time and Day Correlates

Variables	Counterfeit (1)	Substandard (2)	Counterfeit (3)	Substandard (4)	Counterfeit (5)	Substandard (6)
Morning	0.029	−0.028	0.029	−0.026	0.031	−0.021
	(0.052)	(0.020)	(0.052)	(0.020)	(0.051)	(0.021)
Afternoon	0.015	−0.003	0.012	−0.002	0.008	−0.002
	(0.041)	(0.020)	(0.040)	(0.020)	(0.040)	(0.020)
Weekend	−0.043	−0.039∗	−0.045	−0.039∗	−0.036	−0.040∗
	(0.042)	(0.022)	(0.042)	(0.022)	(0.041)	(0.021)
Constant	0.174∗∗∗	0.059∗∗∗	0.191∗∗∗	0.060∗∗∗	0.137∗∗∗	0.011
	(0.040)	(0.022)	(0.040)	(0.023)	(0.052)	(0.029)
Drug Type Fixed Effects			X	X	X	X
Shopper Fixed Effects					X	X
Observations	879	879	879	879	879	879
R-squared	0.053	0.1	0.065	0.104	0.098	0.122

Notes: Regressions are linear probability models controlling for a parish fixed effect. "Counterfeit" refers to a purchased dosage in which at least one tablet failed the handheld spectrometry test; "Substandard" refers to a purchased dosage in which at at least one tablet failed the handheld spectrometry test and also did not match any other brands within the library. The time refers to the time at which the drug was purchased. Morning refers to a time before noon; afternoon is between noon and 5:00pm; the omitted category is evening. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.7: Real Customer Correlates

Variables	Sold Counterfeit (1)	Sold Substandard (2)	Sold Counterfeit (3)	Sold Substandard (4)
Average Malaria Score	0.131	−0.045	0.063	−0.1
	(0.152)	(0.079)	(0.164)	(0.086)
Average Repeat Customer	0.026	0.01	0.074	0.025
	(0.081)	(0.042)	(0.085)	(0.045)
Average Price Paid	0.021	0.002	0.026	0.005
	(0.023)	(0.012)	(0.024)	(0.013)
Average Ln Income	−0.013	−0.004	−0.019	−0.016
	(0.033)	(0.017)	(0.038)	(0.020)
Average Distance	0.001	−0.001	0.001	0
	(0.002)	(0.001)	(0.002)	(0.001)
Average Adult Patients	0.183∗	0.003	0.276∗∗	−0.009
	(0.107)	(0.055)	(0.116)	(0.061)
Average Female Customers	−0.078	−0.071∗	−0.074	−0.070∗
	(0.074)	(0.039)	(0.078)	(0.041)
Constant	0.012	0.129	−0.043	0.205∗
	(0.190)	(0.099)	(0.209)	(0.110)
District Fixed Effect	X	X		
Parish Fixed Effect			X	X
Observations	277	277	277	277
R-squared	0.043	0.027	0.162	0.119

Notes: The sample is all outlets with at least one survey of a real customer. "Sold Counterfeit" refers to whether a drug classified as counterfeit was ever sold from that outlet during mystery shopping. "Sold Substandard" refers to whether a drug classified as substandard was ever sold from that outlet during mystery shopping. All independent variables are from the surveys of real customers, averaged at the shop level. Malaria score is an average of 6 questions regarding malaria transmission. Repeat customer is whether the respondent reported ever shopping at that outlet before. Price paid is the price in USD for the primary product. Ln Income is the log of the respondent's reported monthly income. Distance is measured in minutes walking to get to this establishment. Adult patient is whether the respondent reported buying their medicine for a child in the household. Female customer refers to whether the respondent was male or female. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.8: Drug Quality and Establishment Type

Variables	Sold Counterfeit (1)	Sold Substandard (2)	Sold Counterfeit (3)	Sold Substandard (4)	Average Shop Price (5)	Qualified Person (6)	License on Display (7)	#Antimalarials Stocked (8)
Clinic	0.075	−0.012	0.069	−0.026	0.718***	−0.409***	0.261***	−6.781***
	(0.091)	(0.048)	(0.099)	(0.058)	(0.184)	(0.095)	(0.065)	(0.696)
Drug shop	0.021	−0.036	0.032	−0.039	0.357**	−0.448***	0.461***	−6.872***
	(0.095)	(0.051)	(0.103)	(0.061)	(0.160)	(0.105)	(0.083)	(0.792)
Constant	0.210**	0.081*	0.212**	0.088	2.545***	0.739***	0.015	11.753***
	(0.086)	(0.046)	(0.093)	(0.056)	(0.139)	(0.090)	(0.062)	(0.693)
Observations	459	459	405	405	405	405	405	405
R-squared	0.078	0.083	0.09	0.073	0.259	0.2	0.189	0.438

Notes: Sample in first two columns is all outlets where a drug was purchased and could be tested for quality. Sample in remaining columns is all outlets at which there was a survey completed, and excludes missing values/don't know/don't recall. "Clinic"/"Drug shop" is recorded from the census; the omitted category is "Pharmacy/Other". "Sold Counterfeit" refers to whether a drug classified as counterfeit was ever sold from that outlet during mystery shopping. "Sold Substandard" refers to whether a drug classified as substandard was ever sold from that outlet during mystery shopping. "Average Shop Price" is the average price paid during mystery shopping among all purchases. "Qualified person" is whether the respondent was estimated to meet the legal qualifications to dispense medicines according to the legal standards. It is assessed from responses based upon years of experience, education, and type of establishment. "License on Display" was whether the enumerator marked that during the vendor survey there was a license on display. "No. Antimalarials in Stock" refers to the number of antimalarials listed on the drug inventory portion of the drug vendor survey. All regressions include a parish fixed effect. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.9: Facility Observations

Variables	Counterfeit Sold (1)	Substandard Sold (2)	Counterfeit Sold (3)	Substandard Sold (4)
Manual or No System	0.304***	−0.078***	0.309***	−0.079***
	(0.107)	(0.029)	(0.107)	(0.029)
All inventory protected from sunlight	0.075	0.036	0.064	0.035
	(0.071)	(0.022)	(0.072)	(0.024)
Crowded store	−0.033	−0.052**	−0.03	−0.053**
	(0.063)	(0.026)	(0.064)	(0.026)
Concrete floor	−0.183**	−0.002	−0.197**	0.002
	(0.091)	(0.044)	(0.091)	(0.044)
Establishment was very clean	−0.012	−0.021	−0.006	−0.025
	(0.059)	(0.032)	(0.060)	(0.031)
Inventory on floor	−0.135*	−0.061**	−0.147*	−0.060**
	(0.081)	(0.028)	(0.084)	(0.029)
Above Average Quality	0.111	0.038	0.106	0.037
	(0.159)	(0.121)	(0.160)	(0.121)
Average Quality	0.094	−0.031	0.088	−0.033
	(0.158)	(0.116)	(0.160)	(0.116)
Below Average Quality	0.037	−0.04	0.028	−0.044
	(0.161)	(0.117)	(0.164)	(0.118)
Far Below Average Quality	0.011	0.017	0.011	0.004
	(0.178)	(0.129)	(0.184)	(0.133)
Drug Shop			0.029	−0.033
			(0.111)	(0.067)
Clinic			0.078	−0.026
			(0.104)	(0.063)
Constant	0.297	0.075	0.276	0.106
	(0.205)	(0.125)	(0.234)	(0.145)
Observations	409	409	409	409
R-squared	0.135	0.125	0.138	0.125

Notes: Sample is all outlets at which there was a survey completed, and excludes missing values/don't know/don't recall. Data are from the observations of the enumerator after the conclusion of the survey. "Manual or no system" refers to whether the enumerator observed a manual inventory and record-keeping system, or no system. This variable is a zero for hybrid systems or computerized record-keeping. "All inventory protected from sunlight" is a dummy variable indicating that the entire stock of inventory was not exposed to direct sunlight. "Crowded store" is whether the enumerator judged that the store had adequate space to display its inventory. "Concrete floor" is a variable indicating whether the floor was concrete, as opposed to a dirt floor. "Establishment was very clean" is a subjective measure by the enumerator about the cleanliness of the outlet. "Inventory on floor" was whether the enumerator noted that there were boxes of inventory stored on the floor of the outlet, as opposed to shelves or cabinets. All regressions include a parish fixed effect. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.10: Supply Networks

	Counterfeit Sold	Substandard Sold	Counterfeit Sold	Substandard Sold	Counterfeit Sold	Substandard Sold
Ever bought stock from:	(1)	(2)	(3)	(4)	(5)	(6)
Drug Promoter	0.077	0.122	0.079	0.122	0.078	0.117*
	(0.109)	(0.075)	(0.108)	(0.075)	(0.093)	(0.069)
Wholesale Pharmacy	−0.101	−0.048	−0.102	−0.042	−0.001	−0.009
	(0.141)	(0.067)	(0.143)	(0.071)	(0.125)	(0.063)
Retail Pharmacy	0.102	−0.028	0.102	−0.023	0.087	−0.032
	(0.063)	(0.023)	(0.064)	(0.024)	(0.061)	(0.024)
Drug Shop			0.011	−0.025	0.018	−0.035
			(0.097)	(0.061)	(0.086)	(0.052)
Clinic			−0.015	−0.045	0.015	−0.041
			(0.092)	(0.059)	(0.082)	(0.053)
Constant	0.333**	0.098	0.333**	0.122	0.224	0.097
	(0.141)	(0.066)	(0.160)	(0.079)	(0.144)	(0.072)
Parish FE	X	X	X	X		
District FE					X	X
Observations	415	415	415	415	415	415
R-squared	0.092	0.09	0.092	0.093	0.016	0.031

Notes: Data are taken from survey responses to the drug vendor survey where a purchase was made that could be tested(N=416). "Sold Counterfeit" refers to whether a drug classified as counterfeit was ever sold from that outlet during mystery shopping. "Sold Substandard" refers to whether a drug classified as substandard was ever sold from that outlet during mystery shopping. Each variable is a dummy variable indicating whether the respondent ever purchased stock from a given type of wholesaler. Multiple responses were allowed. Regressions control for either a parish or a district fixed effect. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.11: Other Outlet Characteristics

Variables	Counterfeit Sold (1)	Substandard Sold (2)	Counterfeit Sold (3)	Substandard Sold (4)	Counterfeit Sold (5)	Substandard Sold (6)
No name visible	0.073	−0.005	0.053	−0.011	−0.018	−0.026
	(0.067)	(0.038)	(0.071)	(0.040)	(0.059)	(0.034)
Any agency visit	−0.005	−0.055	−0.012	−0.056	0.019	−0.045
	(0.071)	(0.045)	(0.070)	(0.047)	(0.060)	(0.042)
Profits, USD	0.001	−0.01	0.007	−0.013	0.01	−0.013∗
	(0.021)	(0.006)	(0.020)	(0.008)	(0.018)	(0.008)
Business training program	−0.026	0.005	−0.029	0.012	−0.013	0.021
	(0.053)	(0.031)	(0.055)	(0.031)	(0.049)	(0.029)
Any debt	0.110∗	0.017	0.112∗	0.015	0.101∗	0.008
	(0.065)	(0.034)	(0.065)	(0.035)	(0.060)	(0.031)
Debt question nonresponse	0.042	0.143	0.06	0.147	0.059	0.12
	(0.155)	(0.112)	(0.155)	(0.115)	(0.145)	(0.112)
Number of employees	0.011	0.002	0.017	0.001	0.021∗	0.002
	(0.013)	(0.006)	(0.013)	(0.007)	(0.012)	(0.006)
Have beds	−0.002	−0.055∗	−0.017	−0.01	−0.028	−0.037
	(0.068)	(0.032)	(0.093)	(0.045)	(0.081)	(0.041)
Test for malaria	(0.073)	0.038	−0.076	0.043	−0.088	0.045
	(0.066)	(0.034)	(0.065)	(0.035)	(0.058)	(0.031)
Charge consultation fee	0.086	−0.041	0.066	−0.03	0.068	−0.034
	(0.080)	(0.029)	(0.082)	(0.027)	(0.076)	(0.024)
Constant	0.203∗∗	0.101∗∗	0.066	0.141	0.015	0.137∗
	(0.085)	(0.050)	(0.132)	(0.088)	(0.111)	(0.076)
Parish Fixed Effect	X	X	X	X		
Establishment Type Fixed Effect					X	X
District Fixed Effect					X	X
Observations	370	370	370	370	370	370
R-squared	0.109	0.096	0.115	0.102	0.055	0.045

Notes: Sample is all outlets with a completed survey. "Counterfeit Sold" is whether a counterfeit drug was sold at that outlet during mystery shopping. "Substandard Sold" is whether a substandard drug was sold from that outlet. "No name visible" indicates whether there is a printed sign. "Any agency visit" is whether any regulator, including the NDA, had visited over the past 6 months. "Profits" are self-reported monthly profits, reported in 1000 USD. The exchange rate is $US1 = 2593 UGX. "Any debt" indicates the establishment has debt; "Debt question nonresponse" indicates vendor nonresponse. "Have beds" indicates whether the establishment has beds to treat patients; "Test for malaria" indicates whether testing is available at the outlet; "Charge consultation fee" is whether the respondent reported that the outlet ever charged a consultation fee to diagnose illnesses. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.12: Competition

Variables	Counterfeit Sold (1)	Substandard Sold (2)	Counterfeit Sold (3)	Substandard Sold (4)	Counterfeit Sold (5)	Substandard Sold (6)
Public Health Facility	−0.220***	−0.002	−0.237***	−0.002	−0.238***	−0.015
	(0.077)	(0.057)	(0.079)	(0.057)	(0.080)	(0.055)
# Drug Shops	−0.012**	−0.006**	−0.013**	−0.006**	−0.013**	−0.006**
	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.003)
# Clinics	−0.018	−0.005	−0.015	−0.007	−0.014	−0.005
	(0.022)	(0.009)	(0.023)	(0.011)	(0.024)	(0.011)
# Pharmacies	−0.021	−0.031**	−0.019	−0.031**	−0.022	−0.056***
	(0.042)	(0.016)	(0.043)	(0.016)	(0.049)	(0.021)
HHI Village	−0.213	−0.155**	−0.283*	−0.191**	−0.281*	−0.189**
	(0.131)	(0.064)	(0.149)	(0.080)	(0.149)	(0.080)
Minimum Distance to Public			−0.001	0.000	−0.001	0.000
			(0.001)	(0.000)	(0.001)	0.000
Minimum Distance to Private			0.003	0.001	0.003	0.001
			(0.003)	(0.001)	(0.003)	(0.001)
Drug Shop					0.000	−0.099
					(0.109)	(0.071)
Clinic					−0.022	−0.116*
					(0.106)	(0.070)
Constant	0.494***	0.169***	0.526***	0.176***	0.535***	0.279***
	(0.086)	(0.052)	(0.096)	(0.056)	(0.138)	(0.091)
Observations	433	433	415	415	415	415
R-squared	0.116	0.109	0.129	0.108	0.129	0.12

Notes: "Sold Counterfeit" refers to whether a drug classified as counterfeit was ever sold from that outlet during mystery shopping. "Sold Substandard" refers to whether a drug classified as substandard was ever sold from that outlet during mystery shopping. Columns 3-6 are conditional on survey completion. Public health facility is a dummy variable indicating whether there is a facility in that village. HHI Village corresponds to the Hirfindahl-Hirshman Index of market concentration, where the market is defined to be the village. Higher values indicate a more concentrated market. Minimum distance to public/private is the respondent's answer of the minutes walking to the nearest public/private facility. Respondents who did not know or refused to answer were imputed to be equal to the median with a dummy variable indicating the imputation included in the regression. Drug shop and clinic refer to the self-designated establishment type. Robust standard errors in parentheses. All regressions include a parish fixed effect.$***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.13: Balancing Table for List Randomization

	Ever Bribed NDA			Sold Antibiotics When Unnecessary			Sold Fake Drug		
	T (N=200)	C (N=224)	Diff	T (N=205)	C (N=219)	Diff	T (N=224)	C (N=200)	Diff
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Male	0.20	0.25	−0.05	0.30	0.16	0.14***	0.16	0.30	0.14***
Correctly answered math question	0.42	0.41	0.01	0.42	0.40	0.02	0.40	0.43	−0.03
Runyankole	0.52	0.49	0.02	0.36	0.38	−0.02	0.52	0.48	0.04
Luganda	0.34	0.32	0.02	0.51	0.50	0.01	0.31	0.35	−0.04
Owner	0.38	0.36	0.01	0.34	0.33	0.01	0.33	0.41	0.08*
Respondent born in parish	0.10	0.09	0.01	0.11	0.08	0.03	0.09	0.10	−0.02
Distance to closest competitor	6.93	6.87	0.06	7.15	6.65	0.50	6.42	7.43	−1.01
Distance to closest public health facility	43.32	37.52	5.80	33.08	47.10	−14.02**	37.09	43.80	−6.71
Inspected by regulator in past 6 months	0.84	0.88	−0.04	0.85	0.87	−0.02	0.88	0.84	0.03
Profits in past month, USD	274.56	339.88	−65.32	354.42	265.85	88.57	244.85	381.35	−136.50
Malaria Transmission Test Score	0.83	0.80	0.02	0.82	0.81	0.02	0.81	0.81	0.00
Years of Experience	6.86	6.03	0.83	6.26	6.57	−0.32	6.42	6.42	0.00
Clinic	0.41	0.43	−0.02	0.42	0.42	0.00	0.42	0.42	0.00
Drug Shop	0.52	0.53	−0.01	0.52	0.53	−0.02	0.52	0.53	−0.01
Qualified person	0.35	0.39	−0.04	0.40	0.35	0.05	0.37	0.38	−0.01

Notes: Above are sample mean averages from the vendor survey, excluding missing values. The Control group (C) was shown a list of non-sensitive activities; the Treatment group (T) was showing the same list with an additional sensitive activity. This exercise was conducted for three different sensitive activities. "Bribe" refers to the sensitive activity, which was listed in the following way: "Bribed an official or inspector from the NDA to get out of trouble or a fine." "Antibiotics" was listed in the following way: "Sold antibiotics or other drugs to a customer when I knew it was unnecessary."; "Fake Drug" was listed in the following way: "Ever sold a drug to someone that I knew was fake." "Runyankole"/"Luganda" are indicator variables for the language that the survey was conducted in. "Owner" is a dummy variable and based upon self-reported value by respondent. Distance variables are recorded as minutes spent walking. "Inspected by regulator in past 6 months" is a dummy variable referring to whether the respondent reported having a visit by any government regulator of any agency in the past six months. "Profits" are self-reported profits in the past, reported in USD. The approximate exchange rate at the time of data collection is $US1 = 2593 UGX. "Malaria transmission test score" is the average score of the respondent on the malaria transmission module of the survey. "Years of Experience" is the years the respondent reported being in this line of work. "Clinic"/"Drug shop" is taken from the census. "Qualified person" is whether the respondent was estimated to meet the legal qualifications to dispense medicines according to the legal standards. It is assessed from responses based upon years of experience, education, and type of establishment. Significance levels conditional on a district fixed effect. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.14: List Randomization Results

Variables	Bribe # Activities (1)	Antibiotics # Activities (2)	Fake Drug # Activities (3)
Treatment	0.172*	0.056	0.073
	(0.102)	(0.105)	(0.087)
Male	0.421***	0.426***	0.558***
	(0.115)	(0.128)	(0.100)
Minimum Distance to Public	0.004	−0.017	0.008
	(0.128)	(0.123)	(0.105)
List Randomization Form Dummy	0.318	−0.056	0.225
	(0.251)	(0.267)	(0.360)
Owner	0.055	0.106	0.329***
	(0.114)	(0.109)	(0.095)
Constant	2.696***	2.265***	2.052***
	(0.107)	(0.111)	(0.109)
Observations	440	440	440
R-squared	0.76	0.057	0.23
Dep Variable Mean, Control	2.87	2.36	2.38

Notes: Sample is all respondents who completed a survey, and excludes those with missing values for any variable in the regression. Robust standard errors in parentheses. Above are OLS estimates from a linear probability model of a list randomization exercise. The dependent variable in all columns is the number of activities that the respondent has reported doing. The treatment group was shown the same list of non-sensitive activities as the control group, plus one sensitive activity. The sensitive activity in Column 1 is "ever paid a bribe to a regulator (NDA)"; the sensitive activity in Column 2 is "ever sold antibiotics to a customer when they knew it wasn't needed"; the sensitive activity in Column 3 is "ever sold a fake drug". "Treatment" indicates whether the respondent was randomly assigned to the treatment group (ITT). All regressions control for a district fixed effect and select covariates. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 2.15: Vendors Recommendations for Reducing Fake Drug Rates

Panel A: Vendor recommendations for penalties		
	Recommended fine	385.65
	Recommended jail sentence	8.71
Panel B: Rank/Percentage of respondents stating the policy will work.		
1	Increase training programs for vendors and pharmacists	0.973
2	Increase inspections at borders and points of entry	0.949
3	Increase inspections at outlets (NDA)	0.907
4	Increase fines for those who are caught	0.873
5	Increase jail sentences	0.849
6	Customer education campaigns	0.798

Notes: Data are taken from survey responses to the drug vendor survey (N=451). In Panel A, the recommended fine is in USD, and the exchange rate used is $1US=2593 UGX. The jail sentence for those who said that the sentence should be "life" was top-coded at 99. In Panel B, responses for each possibility included: 1 ("will definitely not work"); 2 ("will likely not work"); 3 ("will likely work"); 4 ("will definitely work"). Above are averages of respondents who agree that a given policy either will definitely work or will likely work. Multiple responses were allowed.

Table 2A.1: Spectrometry Testing Transition Matrix

Panel A: Tablet Level (N=2322)		
	Second Scan Outcome	
First Scan Outcome	Pass	Fail
Pass	0.297	0.007
	N = 689	N=16
Fail	0.177	0.519
	N = 411	N=1206

Panel B: Transaction Level (N=879)		
	Second Scan Result	
First Scan Result	Non-Counterfeit	Counterfeit
Non-Counterfeit	0.76	0.00
	N=665	N=0
Counterfeit	0.07	0.18
	N=59	N=155

Notes: In total, there were 879 purchases of antimalarial drugs which could be tested using the handheld spectrometer. A full adult dosage of artemether-lumefantrine contains 24 tablets, a full adult dosage of sulphadoxine-pyrimethamine contains 3 tablets, and a full dosage of quinine contains 30 tablets. There were 23,083 tablets scanned with the handheld spectrometer, and 2,322 were scanned at least twice. In Panel A, the sample is restricted to all tablets that were scanned twice. Each cell represents the marginal distribution/probability of passing or failing the first scan, and then the second scan. In Panel B, the sample is all purchases. Each cell represents the marginal distribution of results based upon the first scan of each tablet, and the second scans of each tablet (if multiple scans were performed).

Table 2A.2: Real Shopper Data Summary

Panel A: Purchase Data	Sample Average
Did not buy anti-malarial drug	0.55
Bought anti-malarial drug	0.45
Among those buying an antimalarial drug:	
Bought AL	0.60
Bought quinine	0.12
Bought SP	0.20
Product price	2.54
Panel B: Demographic Data	
Asked for diagnosis	0.61
Asked for recommendation	0.51
Less primary school	0.30
Secondary school	0.45
Distance from outlet	21.85
Malaria literacy score	0.72
Income	133.04
Female	0.50

Notes: Above are sample averages from the surveys of real customers at outlets (N=867) exclude missing values/nonresponse. AL stands for artemether-lumefantrine; quinine refers to quinine sulphate; SP refers to sulphadoxine-pyrimethamine. Distance from shop is measured in minutes walking. Malaria literacy is an average of 6 questions of understanding of malaria transmission. Income and price paid is reported in 2013 USD. The exchange rate used was $1US= 2593 UGX.

Table 2A.3: Mystery Shopper Data Summary

Panel A: Characteristics	Sample Average
Age	34.14
Number of Visits	56.44
Female	0.50
Tribe:	
Banyankole	0.438
Bakiga	0.188
Konzo	0.188
Baganda/Other	0.188

Notes: Above are sample averages self-reported by mystery shoppers. In instances where shoppers were of more than 1 tribe, the mother's tribe was used.

Table 2A.4: Discrimination

	Denied Sale	Bought AL	Made Recom-mendation	Bargained	Offered Additional Products	Price Offer USD	Price Paid USD	Service Quality Index
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Minority Tribe	0.001	−0.072**	0.003	−0.012	−0.059	−0.126	−0.169	0.331***
	(0.001)	(0.033)	(0.062)	(0.050)	(0.052)	(0.169)	(0.161)	(0.044)
Female Shopper	−0.003	−0.011	−0.053	0.143***	−0.252***	0.164**	0.012	0.032
	(0.003)	(0.019)	(0.042)	(0.037)	(0.035)	(0.072)	(0.063)	(0.034)
Constant	0.002	0.950***	0.572***	0.520***	0.832***	3.431***	3.112***	−0.237***
	(0.002)	(0.021)	(0.034)	(0.033)	(0.027)	(0.071)	(0.063)	(0.025)
Observations	879	879	879	879	879	879	879	867
R-squared	0.077	0.195	0.03	0.156	0.133	0.233	0.213	0.322

Notes: Coefficient estimates are marginal effects from a linear probability model. All columns control for a parish fixed effect. The sample is all purchases that could be tested for quality. Same Tribe and Minority Tribe refer to the tribe of the shopper. Minority tribe is specific to each district's most prevalent ethnic group. Robust standard errors in parentheses,clustered at the outlet level. $***p < 0.01, **p < 0.05, *p < 0.1$

Chapter 3: The Spillover Effects of Health Insurance Within Families: Experimental Evidence from Nicaragua

3.1 Introduction

Rather than modeling the demand for health care from the perspective of an individual agent, a growing literature considers how households make decisions about healthcare utilization. Empirical work has shown that parental behavior in particular is an important determinant of health and health behavior of their children. For example, consider the decision to enroll in health insurance- an important determinant of healthcare utilization and ultimately health outcomes (Olson et al., 2005). Eligible children with insured parents are more likely to be enrolled in health insurance themselves, more likely to

receive necessary care and more likely to receive regular checkups (Davidoff et al., 2003; Hanson, 2001; Lambrew, 2001; Guendelman et al., 2006; Guendelman and Pearl, 2004). Much of the research focusing on household dynamics and health insurance presents these types of static associations, demonstrating the high correlation between health behaviors within families. However, it is less clear how households allocate and reallocate healthcare amongst their children as family resources and needs change. Understanding the effects of intra-household healthcare allocation not only sheds light on the complex dynamics of household decision-making, but also is important for designing health policies that reduce unmet need for healthcare, and ultimately improve health and well-being.

From a theoretical perspective, there are several ways that health insurance could affect the utilization of a household. If insurance improves health or preventive care (e.g., vaccinations) then there may be positive externalities among uninsured members of the household. For example, insured individuals may be less likely to infect their siblings. As a result, ineligible siblings might not require as many visits to healthcare providers. However, effects on other household members do not depend on health insurance improving health. Decreases in the price of health care will likely increase healthcare utilization and reduce out of pocket expenditures among individuals who are insured. If individuals within a family share a common budget and time constraint, then a change in the price of healthcare for one member will cause a reallocation of both time and financial resources for all members due to

both the income and substitution effects.[82] This prediction holds whether one assumes a unitary model of household production or instead that the allocation of health investments is the result of cooperative bargaining (Bolin et al., 2001).Therefore, the equilibrium distribution of health demand for all family members will change following enrollment into health insurance, even if the individual is excluded from health insurance coverage. In the context we study here, both the direction and magnitude of the spillover depends upon the structure of the family health production function (i.e., whether siblings are complements or substitutes).[83]

However, empirically identifying both direct and spillover effects of health insurance is difficult. First, selection into insurance take-up provides challenges for researchers using retrospective data because health insurance enrollment is likely correlated with other characteristics of a household. Standard theoretical models, as well as empirical studies, posit adverse selection into health insurance: individuals who are more likely to be sick, and will benefit more from insurance are those who enroll (Oster et al., 2010; Einav and

[82]This theory is formalized by Jacobson (2000) as an extension of the standard Grossman (1972) model. This model predicts that parents will not equalize health status amongst all members of a household. Instead, the model predicts that parents will choose the optimal health inputs such that the ratio of marginal benefits to marginal cost are equal across all family members.

[83]There is a related of literature related to how parents allocate resources among their children. Evidence is mixed as to whether parents differentially favor certain children behavior on the basis of health endowments or labor market opportunities (Adhvaryu and Nyshadham, 2014; Jensen and Miller, 2013; Li et al., 2010; Behrman and Rosenzweig, 2004). Duflo (2003) finds that when women have more bargaining power in a household, female children benefit more than male children. Jason Fletcher (2012) find that siblings with disabilities negatively affect the education attainment of siblings.

Finkelstein, 2011; Levine et al., 2011). On the other hand, recent evidence has found advantageous selection into some health insurance markets, where the most responsible, healthiest, or most knowledgeable individuals choose to enroll (Fang et al., 2008). Second, measuring intra-household resource allocation requires detailed individual-level data on utilization. However, data are typically collected only at the household level, making it impossible to study within-family spillovers. Although there are studies that correct for selection into health insurance through randomized designs, these studies have focused on the household or individual direct effects of health insurance ((King et al., 2009; Levine et al., 2011; Finkelstein et al., 2012; Sheth, 2014; Newhouse, 1993; Asuming, 2013). As a result, there have been few studies addressing the intra-household dynamics and behavior following insurance coverage.

To overcome these empirical challenges, we utilize an experiment that randomly assigned free health insurance to informal-working adults in urban Nicaragua. In addition to giving comprehensive coverage to the primary holder of the insurance, the plan gave coverage to children who were under the age of 12. We use the randomized experiment and the age eligibility cutoff for dependents to identify causal effects of parental health insurance on both covered and uncovered children. We empirically assess how healthcare utilization changes after one year, where we measure utilization with number of visits, out-of-pocket expenditures, and choice of health provider. We also include several self-reported health measures.

We find that age-eligible children whose parents receive insurance increase their total healthcare utilization by 1.3 visits, a 39 percent increase. We find insurance increases utilization at covered providers by 0.56 visits (a 360 percent increase). In addition, total utilization by insured children increases by 1.26 visits (37 percent increase over the control group). Our results indicate that health insurance was used to complement existing utilization patterns among insured children, as opposed to substituting towards covered providers.

However, there is a substantial and large negative spillover onto uninsured older children in insured families. Older, uninsured children with insured parents/siblings decrease their total health visits by 3.4 visits (an 80% reduction). There are also significant reductions in visits to and spending at private facilities in response to parental health insurance. We find similar reductions in out of pocket expenditures, consistent with the changes in utilization. We provide evidence that health insurance also change where ineligible children sought treatment. Conditional on being sick, ineligible children in insured households are substantially more likely to seek treatment at pharmacies as opposed to private providers.

Next, we examine the effects on reported health indicators. Among eligible children, we find no impact of the insurance on the likelihood of being sick or in the severity of sickness. However, we find that health insurance coverage resulted in 0.68 additional sick episodes (37 percent increase). There was no significant impact on checkups or the likelihood of forgoing treatment. On

the other hand, among ineligible children, sickness decreased by 1.06 episodes (58 percent decrease) and these children were significantly less likely to be reported to have forgone treatment due to lack of money. We discuss several possible explanations for these results, and conclude that the changes in reported health status are most likely due to improved information on actual health status through interaction with high-quality providers.

We then present two sets of analyses to further understand the nature of within family spillovers and their effects on health. First, we examine the extent to which the spillover to ineligible children is driven by parent coverage or sibling coverage.[84] Our results suggest that the relationship between parental and child utilization is stronger than across-child utilization. This paper contributes to the existing literature by empirically assessing how parental health insurance affects the healthcare utilization and health outcomes for both covered and uncovered children. Existing studies have either focused on how parental insurance eligibility affects the enrollment of eligible children, or how children who are ineligible for health insurance enjoy health benefits by being in insured households. For example, previous work on Medicaid expansions in the United States has found positive spillovers of parental health insurance coverage on the enrollment of children in health insurance (Dubay and Kenney, 2003; Sommers et al., 2012; Cutler and Gruber, 2001; Aizer and Grogger, 2003; Busch and Duchovny, 2005). Ishdorj et al. (2007)

[84]We do not focus on outcomes for parents in this paper; rather, these results can be found in Thornton et al. (2010).

and Basiotis (1998) both find evidence supporting positive intra-household spillovers of a supplemental insurance program in the United States (WIC), among ineligible family members. Two studies that use an age-eligibility cut-off to examine how WIC affected older, age-ineligible children also find positive effects. Ver Ploeg (2009) finds positive health effects and Robinson (2012) finds increases in nutritional intake among ineligible children (older than five) when their siblings are eligible for WIC. Few studies have causally estimated the effect of parental health insurance on children's utilization, and to our knowledge no prior study has causally estimated the spillover effects of health insurance on the utilization of uninsured members. This gap is surprising because many health insurance programs have age-eligibility cutoffs, and the magnitude of the effect of insurance on both insured and uninsured members has implications for the sustainability and cost-effectiveness of programs (Basu and Meltzer, 2005).

3.2 Background

3.2.1 Health Insurance in Nicaragua

In Nicaragua, formal sector employees are eligible to enroll in the Nicaraguan Social Security Institute (INSS) health insurance program. The INSS insurance provides all subscribers with a comprehensive package of preventive, diagnostic, and curative health services and medications at 17 INSS-contracted facilities in Managua (formerly called Empresas Médicas Previsionales, re-

ferred to as EMPs). The services provided include primary and specialist care, medication and laboratory exams, hospitalization, 24-hour emergency care, voluntary family planning counseling and contraception, breast and cervical cancer screenings, HIV and STD counseling, and prevention and treatment of dengue fever and malaria. There are no co-pays at the time of service; rather, individuals who enroll pay a monthly flat fee of approximately $15 to the Social Security Institute for coverage. In addition to the subscriber, the subscriber's wife is eligible for maternity services, including prenatal care, childbirth and postnatal care. Dependent children under the age of 12 are also fully covered for pediatric care and vaccinations; children under age 5 also qualify for child wellness visits. Children over the age of 12 are excluded from coverage.[85]

While this insurance plan covers those in the formal sector, this represents only a small proportion of the adult population- just under half a million adults or approximately 13.5 percent of the adult population (Instituto Nacional de Información de Desarrollo INIDE and). Options for healthcare are limited among uninsured, informal sector workers. Uninsured individuals have access to free public sector clinics and hospitals run by the Ministry of Health Services (MINSA). However, these services are often under-resourced

[85]Available evidence suggests that this age cutoff is strictly enforced. EMPs are only able to be reimbursed for services if they can document that the individual was enrolled in the health insurance; that is, if the child is under 12. Any medical or labor expenses incurred on ineligible children would not have been paid by the INSS program. Since these facilities are for-profit, it is unlikely that they would have given away any medical care for free.

and the source of complaints of long waiting times, frequent supply stockouts, and generally poor quality (Magnoni et al., 2005). Rather than seeking treatment at MINSA facilities, self-medication from pharmacies for basic care is common. For those who can afford it, higher quality, more expensive private facilities are available. On the other hand, many are unable to pay the high out of pocket costs and forgo care altogether. Thus, the INSS health insurance package may not only change the cost but also the quality of healthcare for affected individuals.[86]

3.2.2 The Pilot Program and Evaluation

In January 2007, the government of Nicaragua implemented a demonstration project aimed at extending the Nicaraguan Social Security Institute (INSS) health insurance program to the large population of informal sector workers.[87] Both this paper and Thornton et al. (2010) report results from this evaluation. In 2007, a baseline survey was conducted among randomly selected uninsured informal sector workers in the three largest open-air markets

[86]Higher quality services as a result of health insurance is not unique to the Nicaraguan context. Research from the United States suggests that insurance often changes the quality of service received (Dubay and Kenney, 2001; Howell and Kenney, 2012; Selden and Hudson, 2015). However, the effect of insurance on quality is ambiguous. Insured individuals may substitute away from more expensive high-quality care towards cheaper, covered care. In the case of public healthcare programs, alternatively, insured individuals may substitute away from free, low quality care in the public sector towards higher quality, private providers.

[87]It is estimated that approximately 60 percent of the Nicaraguan workforce is in the informal sector.

in central Managua.[88] The survey asked detailed questions about utilization, spending, and health, for the respondent and each child in the household under the age of 15. The primary objective of the program was to evaluate the demand and impact of health insurance among informal-sector workers. The secondary objective was to test whether allowing insured individuals to pay deductibles at micro-finance institutions (as opposed to government offices) increased enrollment. Coverage and cost was designed to be as similar as possible to those associated with the program for formal sector workers, and enrollment into the program was voluntary.

At the end of the baseline survey, respondents were either given an informational brochure about the insurance product or the brochure plus a six-month subsidy for insurance worth approximately $100, nearly half of the sample median household income.[89] Respondents could enroll in the insurance plan at the INSS or at local micro-finance institutions, and there was no deadline for purposes of this study for enrollment. Upon enrolling, the insurance took effect the first day of the following month. Government ID numbers were collected to match respondents to health insurance enroll-

[88]Respondents were selected with the following two methodologies: in the first phase of the survey, prior to the baseline survey a census of market booths was conducted to define the sampling frame of possible respondents. In the second phase of the survey, interviewers went door to door and sampled each market booth with eligible respondents. Participants deemed eligible through the census were selected randomly (stratified by gender marital status and micro-finance client status) and administered the baseline survey. Individuals who were between ages 18 and 54, had a government ID, were an owner of the market booth, and lacked health insurance coverage were eligible. Overall completion rates were 51 and 53 percent for the two phases.

[89]The original study design also assigned respondents into 2-month subsidy group; these individuals were not in the follow-up survey due to low take-up and budget constraints.

ment data that was to be provided by the INSS.[90] The overall take-up rate of insurance for respondents with insurance-eligible children was 35 percent among those who were offered the six-month subsidy and 2.22 percent among those who were not.[91]

One year later, in 2008, a follow-up study was conducted among the same individuals. Overall, 93 percent of the respondents were re-interviewed (N=2608). There was no differential sample attrition between those who were offered the subsidy and those who were not (Thornton et al., 2010). The authors find that adults with insurance substitute from services at private and Ministry of Health facilities to covered health facilities (EMP), with no statistically significant increases (or decreases) in overall health utilization of services (point estimate 0.918, standard error 0.749) or health. As a consequence, total out-of-pocket expenditures fell by 55 percent when individuals were insured (not statistically significant), with the largest expenditure reductions for private clinics, laboratories, and pharmacies.

[90]The baseline survey also included respondents in four other smaller markets but because these respondents were not followed over time, they are not included in the analysis.

[91]Although this figure may seem low considering the high-value of this product, completing the enrollment process took approximately one full day for respondents, and many of those who did not enroll reported confusion over the enrollment procedures and the benefits (Hatt et al., 2009). Despite these barriers, this take-up rate is in line with results from the Oregon Health Insurance Experiment, which found that low-income individuals who won a lottery for Medicaid for in the United States increased the probability of becoming insured by 25 percentage points (Finkelstein et al., 2012). Similarly, several studies have estimated the marginal take-up rate among U.S. children newly eligible for Medicaid and SCHIP to range from approximately 10 to 30 percent, with average take-up rates ranging by state from 57 percent to 95 percent (Sommers et al., 2012). Therefore, although this population is generally less experienced with insurance products than those in the U.S., this take-up rate may not be context-specific.

3.2.3 Summary Statistics

This paper complements Thornton et al. (2010) by studying how family structure affects health care utilization decisions.[92] Of the 2608 adults/households who were in the initial evaluation (with complete baseline and follow-up surveys), 63 percent had at least one child under the age of 15. Thus our sample consists of 2,996 children in 1614 households in both waves of the survey.[93]

Table 3.1 presents baseline statistics of households (Panel A), parents (Panel B) and children under the age of 15 (Panel C). Summary statistics of children in the three main age categories are shown disaggregated in Appendix A. Parent respondents are 35 years old on average, and have relatively high levels of education (9.3 years), with a median annual income of 3,752 Cordobas (US$207). Among all children in the sample ages 15 and under at baseline, the average age is 8. For most health variables, parents and children have similar averages. Almost all of both parents and children saw a health provider in the past year (76, and 75 percent). The likelihood of

[92]There are at least three reasons why the effect of health insurance might differ between parents and children. First, parents and children have different health levels; children are sick more often than parents. Second, investment into children's health is thought to have higher returns than parental health investments. Third, parents typically control the resources and children cannot typically afford or seek healthcare without consent of the parents.

[93]In comparison with the full sample, respondents with age-eligible children have 0.8 more people in their household, and the same median household income (C$3752), although very different health patterns. Parents report on average C$1360 less for individual health costs than non-parents, and C$500 more in total health costs for their household, although household per-capita health costs are approximately the same. Parents are 0.7 percentage points less likely to be sick than non-parents. Similarly, parents report 1.26 fewer individual visits to all providers, but nearly double the number of total household visits (15 visits and 9 visits, respectively); households with children report 0.77 more health visits per person.

being sick in the past year is similar as well; 77 percent of adults and 76 percent of children were reported ever being sick in the past year. Adults were slightly more likely to have forgone treatment due to lack of money than children (25 percent compared to 18 percent). The average number of visits to all providers for adults was 4.28, compared to 3.82 visits for children. Total average health costs for both parents and children are heavily right-skewed. For children, total costs were nearly C$569, with a median value of C$204; for adults, average costs were C$828, with a median value of C$161. These figures demonstrate that some families experience extremely large health costs.

Among children, these averages mask substantial heterogeneity by age. Younger children, specifically those under 5, are sick approximately 2.8 times per year and report 5.2 total visits to all providers, with an average health care expenditure of C$869 (median:C$322). These averages are substantially higher than the corresponding average at baseline of older children. Children age 6-11 are sick 1.9 times per year and report 3.5 total visits to all providers over the past year, with an average expenditure of C$449 (median: C$107). The total number of visits and expenditures are similar among children 12-15. We now turn to estimating the effects of health insurance by eligibility status.

3.3 Empirical Strategy

To study intra-household effects of insurance coverage, we take advantage of both the insurance randomization and the eligibility age-cutoff. Our main empirical strategy to measure intra- household effects of insurance compares children eligible for insurance coverage due to their age in insured and uninsured households. We categorize children into two main groups- those below age 11 (Eligible), and those age 12-15 (Ineligible for dependent insurance coverage). We correct for potential selection bias with respect to insurance enrollment decisions by using the randomly offered six-month subsidy to instrument for insurance enrollment.

We estimate the following difference-in-difference specification for child i, in family f:

$$\begin{aligned} Y_{if} = \alpha + \beta_1 * \widehat{Insurance}_f + \beta_2 \widehat{Insurance*Ineligible}_{if} + \\ \beta_3 Ineligible_{if} + X'\gamma_+ \epsilon_{if} \end{aligned} \tag{3.12}$$

with the following first stage equations:

$$\begin{aligned} \widehat{Insurance}_f = \alpha + \delta_1 Subsidy_f + \delta_2 Subsidy*Ineligible_{if} + \\ \delta_3 Ineligible_{if} + X'\gamma + \mu_{if} \\ \widehat{Insurance*Ineligible}_{if} = \alpha + \lambda_1 Subsidy_f + \lambda_2 Subsidy*Ineligible_{if} + \\ \lambda_3 Ineligible_{if} + X'\gamma + \eta_{if} \end{aligned}$$

In Equation 3.12, Y_{if} represents utilization or expenditures at health

providers within the past year and Insurance represents whether or not the parent enrolled in insurance. We control for household size, age, gender, parental years of education, whether the child was sick at baseline, income, and whether the child had forgone treatment in the past year due to lack of money to improve precision, and account for potential imbalance with respect to income. We also include market fixed effects to account for the sampling design. However, results are not sensitive to the choice of covariates.[94] We use robust standard errors clustered at the family level to account for correlations in outcomes of interest between family members. All binary outcomes are estimated using a linear probability model.

The estimate of β_1 represents the same direct effect of insurance on insured children under the age of 11 as estimated in equation (1), while β_2 estimates the spillover effect of insurance on children who were in insured families but ineligible for insurance themselves due to an age restriction. This specification also allows us to test whether the total effect of insurance among ineligible kids is equal to zero.

Important to our identification strategy is the random allocation of the subsidy across parents. Table 3.1 provides evidence that randomization was effective with individuals in the subsidy and non-subsidy groups having balanced baseline observable characteristics. For almost every baseline parent-level variable as well as child-level variable, there is no statistically significant

[94]Specifically, there are only two results that change in significance from 5 percent to 10 percent. However, magnitudes change by less than one-hundredth regardless of the specification. Results available upon request.

difference between those whose parent were offered a subsidy, and those who were not (Column 4). These results hold when we consider each of the age groups for children (Appendix Table 3A.1.) The exception is household income is statistically significantly higher in the treatment group compared to the control group. This statistical difference is due to several high outlying values; the median values are identical, and we cannot reject the null hypothesis that the income distributions are the same. Trimming the top 1 percent of income values results in no statistically significant differences between groups.

A second requirement to our instrumental variables approach is that the randomly allocated subsidy is correlated with health insurance enrollment. We present first-stage results in Appendix Table 3A.2 demonstrating that take-up was strongly predicted by the subsidy offer. Eligible children whose parents were offered the six-month subsidy were 31 percentage points more likely to be enrolled. However, parents receiving the subsidy with at least one ineligible child were significantly less likely to be enrolled by 4.6 percentage points.[95] Overall, children in larger households are less likely to be enrolled, and there is a small negative effect on the rate of enrollment among adults in large households. Although a one percent increase in income increases the likelihood of enrollment among all adults by 2.1 percentage points, there is

[95]When including baseline controls, household size and whether the child had forgone treatment in the past year due to lack of income are also significant predictors of enrollment. Age and other indicators of child health are not significantly correlated with enrollment.

no significant linkage between income and enrollment in either the sample of parents or the sample of children. However, in all groups reporting forgoing treatment in the past year due to lack of money is strongly and positively related to health insurance enrollment. The F-statistics from the first-stage equations are 215 and 217, respectively.

Equation 3.12 identifies the both the direct and spillover effects of parental health insurance coverage on children. However, it is unclear whether these spillovers are from parents to children, children to parents, between children, or some combination. To identify the direction of spillovers, we test whether the effect of health insurance enrollment on children differs by children with different family structures. Specifically, we estimate:

$$Y_{if} = \alpha + \beta_1 \widehat{Insurance}_{if} + \beta_2 \widehat{Insurance * Sibling}_{if} + \beta_3 Sibling_{if} + X'\gamma + \upsilon_{if} \tag{3.13}$$

We then measure how eligible and ineligible siblings are affected by estimating this regression separately for those with eligible and ineligible siblings. We instrument Insurance (and the respective interactions) with the randomly assigned subsidy as in Equations 2-4 above.

3.4 Results: Direct and Spillover Effects of insurance

We first present our main results from equation 3.12 by examining health care utilization and expenditures among children both eligible and ineligible for health insurance (Tables 3.2 and 3.3). As would be expected, health insurance increases the likelihood that an eligible child visited an EMP (covered provider) by 23 percentage points, and increases total visits to an EMP by 0.56 visits. Among age-eligible children, health insurance increased total utilization of care at all providers by 1.26 additional visits (38 percent increase).

Among age-ineligible children, we find large negative effects of health insurance on utilization. Children age 12-15 with parents enrolled in the health insurance experience fairly substantial decreases in both the likelihood of visiting providers, and the number of times providers were visited. While not always statistically significant, the interaction term between Insurance and Ineligible is consistently large and negative. Moreover, the net effect of having a parent with insurance on ineligible children for many provider types is large and negative. For example, there is a statistically significant reduction in ever attending a private facility or an EMP (covered provider). Similarly, there are reductions in the number of visits, with a total effect of reducing visits by almost 2 visits (1.8 visits). These reductions are driven primarily through reductions in visits to private facilities, including EMPs, although

all estimated coefficients on interaction terms are negative. In addition to these overall reductions, health insurance also changed patterns of where treatment was sought among ineligible siblings. In Appendix Table 3A.3, we show that (conditional on being sick in the past year), ineligible children are significantly less likely to seek treatment for their last illness at a private doctor or hospital, and instead more likely to seek treatment at a pharmacy.

Turning to expenditures on health, Panel A of Table 3.3 presents results for whether there were any expenditures for a child while Panel B presents results for the amount of spending for a child. To account for the presence of outliers, as well as households with zero expenditures, we consider log expenditures + 1, to include in our sample children with zero costs.[96] The point estimates in Table 3.3 demonstrate that among eligible children, there are no statistically significant effects on expenditures resulting from parental health insurance enrollment. While most of the estimates are imprecise, the majority are small in magnitude. The exception is that ineligible children in insured households are almost 30 percentage points less likely to have ever spent money at private providers, and similarly spend significantly less money at private providers overall. The expenditure results are consistent with the reduction in visits to private providers due to parent insurance enrollment that we found in Table 3.2 among ineligible children.

An issue of primary importance is whether health status improved or decreased as a result of the observed changes in healthcare utilization. In

[96]Forty-two percent of children under 15 have 0 health expenditures in the past year.

Table 3.4, we present the effect of insurance on health status collected from the survey. Among all ages, children with enrolled parents are no less likely to report ever being sick, and are not significantly more likely to ever receive a checkup. While coefficients are negative, there is no statistically significant impact of health insurance on the likelihood of a parent reporting forgoing treatment due to lack of money. We find that age-eligible children are sick 0.67 times more often, significant at the 5 percent level, and miss 3 more days of school (insignificant; p=0.107). The differential effect of parental health insurance among age-ineligible children shows that there are significant spillovers by reported measures of health. There is a strong, negative indirect effect of health insurance among age-ineligible children for the outcome variables "times sick" and "number of days of school missed." However, there is no evidence that the severity of illnesses increased as a result of insurance. The most common last illness reported among all groups is "cold and flu", and there is no difference in diagnoses between Treatment and Control groups.

It is possible that health insurance actually made insured and eligible children sick more often, such as iatrogenic illness from waiting rooms (Steel et al., 1981). However, this interpretation does not fully explain improvements in health among the uninsured. A more plausible explanation is that health insurance instead changed parental reporting patterns of sickness.[97]

[97]The RAND Health Insurance experiment randomized families into different rates of coinsurance with significant changes in healthcare utilization. All individuals were enrolled in health insurance. This experiment also found no significant differences in health

For example, it is possible that parents received better information regarding the child's true health status. Given the substantial increase in visits among eligible children, parents also could have been given advice to keep children who visited the doctor home from school. This explanation, however, does not fully explain why ineligible children missed fewer days of school, or why more accurate health information did not also decrease reported health of older children. Alternatively, it could be that parents use an available heuristic, such as visiting a provider, as a proxy for how often their child is sick. Similarly, if uninsured children visit the doctor less, then this interpretation would also explain the reduction in number of times sick. Available evidence supports this interpretation. In Figure 3.1, we graph the coefficient of the direct treatment effect of health insurance on eligible children by age of child. Graphically it is clear that the results on number of times sick closely mirror the number of visits to all providers. Similarly, the raw correlation at baseline among all children between number of visits and number of times sick is 0.71; at follow-up it is 0.84. In Appendix Table 3A.4, we also show that health insurance did not cause changes in the parent's willingness to seek care (i.e., moral hazard). In other words, health insurance does not change the likelihood of getting sick or ever seeking treatment along the extensive margin, but rather changes how parents recall illness episodes, particularly because it increases overall utilization substantially. These results are also informa-

outcomes among children with increased or decreased utilization patterns due to health insurance (Valdez et al., 1985).

tive as to a potential mechanism of how health insurance affects ineligible children. In particular, these results are inconsistent with the theory that health insurance affects ineligible members through improved health status and fewer contagious diseases.

3.5 Discussion: Spillovers from siblings or parents?

The previous results show that older, age-ineligible children decreased utilization in response to parental health insurance. We now turn to disentangling whether these negative spillovers are due to substitution towards (or from) younger, insured siblings or due to parental health insurance enrollment. The mechanism of the spillover has implications for policy. If the increase in utilization among younger siblings cause decreases in older siblings health utilization, then this suggests that parents have a certain budget allocated to children's healthcare. Thus, these within-family effects would only be observed among child health insurance programs. However, if the spillover comes from the parents, then we would expect our results to be observed whenever parents have insurance, regardless of whether children are insured. We test for heterogeneous effects of health insurance among the sample of eligible/ineligible children with or without eligible or ineligible siblings. These tests support the hypothesis of spillovers from parents onto their children.

We first test whether the effect of health insurance systematically differs

by the eligibility status of siblings. We estimate model (4) on the sample of age-eligible children (N=2172), where we interact the indicator of a parent having insurance with whether the child has an older, ineligible sibling (age 12-15) in the sample. In total 29 percent of children age 11 and under in the sample have at least one sibling age 12-15.

Results presented in Table 3.5 show that having an older, ineligible sibling does not affect the likelihood of ever visiting a provider, but does affect the number of times an eligible child attends a provider. Panel A shows that the likelihood of ever visiting any provider is not significantly related to having health insurance; this effect does not differ by whether the child had an older sibling. The likelihood of visiting an EMP is of the same magnitude as presented in Table 3.2; being enrolled in health insurance increases the likelihood of ever visiting a covered provider by 22 percentage points. At all providers, the likelihood of ever attending a provider does not differ by whether or not the insured child has an older sibling.

Panel B contains estimates for the number of visits at each provider. Column 1 of Panel B shows estimates from the regression on the outcome variable total visits to all providers. Insured children without an older sibling increase their utilization at all providers by 1.905 visits, significant at the 1 percent level. However, insured children with an older sibling have a significantly lower average number of visits: the coefficient on the interaction term of Enrolled Parent*Sibling is significant at the 10 percent level at -3.201 visits. For younger children, it appears that having an older child

in the household mutes the effect of insurance on total utilization, but not the effect of attending a covered provider. One complication with that interpretation, however, is that all insured children also have insured parents. There is no differential effect of having an eligible sibling in the household (not shown).

We next estimate a model among children age 11 and over with or without an eligible sibling. Thus, we effectively shut down the channel of sibling spillovers among those who had decreased utilization. Results are in Table 3.6. Although our sample size decreases to 824, coefficient estimates are suggestive of spillovers from parents. The likelihood of visiting any provider does not differ by whether or not the child had eligible siblings, and point estimates are typically positive- suggesting that eligible siblings, if anything, mute the negative effect on enrollment. Similarly, although the coefficient on Enrolled Parent is still negative for the outcomes of number of visits to a private provider and total number of times sick, these averages do not differ by whether or not there is a younger sibling in the household.

3.6 Conclusion

In this paper we estimate the effect of health insurance on both covered and uncovered children within a household. Children who were covered by their parent's insurance have substantially more visits at covered providers, and increase their total number of visits at all providers combined. We find neither

health improvements nor changes in expenditures among covered children although the time in which they were covered was short. In contrast, children in the same families who were not eligible for coverage due to an age restriction substantially decreased their utilization and spending at private providers and laboratories. These older children are also reported to be healthier than their counterparts in the Control group, suggesting that unmet need did not increase despite the decrease in utilization. We then decompose the spillovers to disentangle whether the effects on older children are primarily due to their younger siblings, or alternatively their insured parents. Our results suggest that the parental channel is stronger than the sibling channel.

This paper provides new insight into how households allocate resources amongst their members. It also demonstrates that the observed correlations of health behaviors between members of the same household do not necessarily imply that health demands, or health outcomes, also typically move together. In contrast, our results are consistent with a model in which parents respond to health insurance by completely adjusting demands of all members- and specifically by decreasing utilization among those for whom healthcare is relatively more expensive.

The findings of our research have interesting implications for providing families with insurance rather than individual insurance for children or adults, in particular for public health programs that aim to improve children's health. Our results suggest that the primary benefit to children of parental health insurance is improved access to care. Parents may be taking

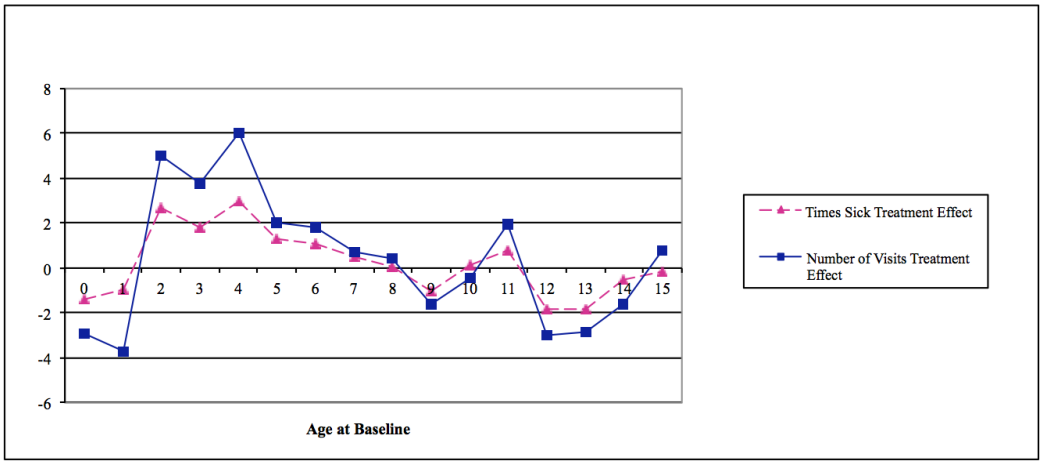
advantage of those visits to have their children seen by doctors for either preventative or curative care. This result was possible because clinics covered by the INSS insurance were full service clinics that included both pediatric and adult services. In the case where covered services are provided by clinics that can treat both adults and children, there can be positive externalities to treating adults on children's health. Additionally, marketing of pediatric services during adult visits may have greater impact as a result. Some inverse spillover may also be occurring whereby parents who take small children to the doctor may use the visit to make appointments for their own future visits. This is a topic for further study but would imply significant benefits to marketing adult preventative and curative care through children's visits when families are uninsured. By utilizing the fact that family members demands are correlated, including parents in children's insurance coverage could be an important step towards reducing unmet need.

However, programs should be carefully designed to avoid unintended consequences, such as negative spillovers on uninsured members of the family. The results of this paper highlight that families allocate resources- including health demands- according to a specified budget and/or time constraint. If utilization increases dramatically among insured members, then it is possible that healthcare demands among uninsured members would fall as a result of health insurance enrollment. While our study was not powered to detect rare or serious ailments among ineligible children, one may assume that reducing healthcare utilization in a resource-poor setting could potentially have true

negative consequences on health.

As health insurance programs, including that of the United States, move towards covering children on health insurance programs, it is important to understand the net benefits and the costs to families from parental health insurance. When considering the effect, and cost-effectiveness of health insurance as a social policy, it may be empirically important to account for the positive as well as the negative effects that influence healthcare demands even uninsured members of the household.

Figure 3.1: Treatment Effect by Age



Notes: Above point estimates are estimated coefficients are from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status. Each treatment effect by age is estimated using a separate regression sample for each age of child. The dependent variable is either the Number of Times Sick, or the Number of Visits. control for household size, household size squared, logged parental income (+1), parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value.

Table 3.1: Baseline Characteristics of Households and Children

	All	No Subsidy (Control)	6-Month Subsidy (Treatment)	Difference (C-T)	P-value Difference
Panel A: Household Characteristics	(1)	(2)	(3)	(4)	(5)
Size of household	4.81	4.76	4.85	−0.09	0.258
Number of children 11 and under	1.34	1.35	1.34	0.01	0.72
Household income	5399	5058	5712	−653.41	0.052
Household income, top 1% trimmed	4791	4699	5003	-304	0.73
Panel B: Parent Characteristics					
Years of education	9.30	9.25	9.36	−0.11	0.624
Ever sick	0.77	0.78	0.76	0.02	0.193
Number of times sick	2.44	2.58	2.31	0.26	0.095
Forgone treatment	0.25	0.25	0.24	0.02	0.446
Ever visit health provider	0.76	0.77	0.75	0.02	0.26
Total number of visits, all providers	4.28	4.46	4.11	0.35	0.26
Total health expenditures	827.76	903.58	758.59	144.99	0.225
Households/Parents (N)	1614	770	844	–	–
Panel C: Child Characteristics					
Age	8.00	7.94	8.06	−0.12	0.459
Female	0.48	0.48	0.49	−0.01	0.473
Ever sick	0.76	0.76	0.77	−0.01	0.843
Number of times sick	2.16	2.19	2.13	0.06	0.602
Forgone treatment	0.18	0.20	0.17	0.03	0.153
Ever visit health provider	0.75	0.75	0.76	0.00	0.983
EMP visits	0.12	0.13	0.11	0.02	0.704
Public health facility visits	0.88	0.89	0.87	0.03	0.679
Private health facility visits	1.04	1.12	0.96	0.16	0.302
Pharmacy visits	1.80	1.80	1.80	0.00	0.916
Total number of visits, all providers	3.82	3.90	3.74	0.16	0.435
Total health expenditures	569.21	533.23	601.76	−68.53	0.302
Children (N)	2996	1423	1573	–	–

Notes: Above are sample averages for the full sample (Column 1), the Control group of respondents/children not awarded a 6 month subsidy for insurance (Column 2), and the Treatment group of respondents/children who were awarded a 6 month subsidy (Column 3). Panels A and B uses the sample of households with at least one child age 15 and under at baseline. All variables except for income are reported averages for the respondent parent. Income is defined as reported monthly household income. Valid income data are not available for 174 families. Panel C uses as the child-level observations, for all children age 15 and under. Health providers consist of EMPs, public clinics, pharmacies, private hospitals, private doctors, public hospitals, and laboratory visits. All health and visit variabes are reported to be during the past year. All income and expenditure data are in 2008 Cordobas. Children who were not sick in the past year are included as zeros for number of times sick and all visit/spending variables. Forgone treatment in past year due to lack of money was calculated to be zero for children who were not sick in the past year. Column (5) represents the p-value from a t-test of means between treatment groups after accounting for the sampling strategy (market and round fixed effects). $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.2: Effects of Parent Insurance on Utilization by Child Eligibility

	Any Provider	Pharmacy	EMP (Covered Provider)	Public Facilities	Private Facilities
Panel A: Ever Visit	(1)	(2)	(3)	(4)	(5)
Parent Enrolled	0.007	0.013	0.226***	0.059	−0.006
	(0.066)	(0.080)	(0.046)	(0.078)	(0.074)
Parent Enrolled*Ineligible Kid	−0.208	−0.158	−0.204***	−0.141	−0.296**
	(0.145)	(0.149)	(0.053)	(0.137)	(0.117)
Ineligible Kid	0.073	0.009	0.019	0.104**	0.050
	(0.048)	(0.049)	(0.017)	(0.044)	(0.039)
Observations	2996	2996	2996	2996	2996
R-squared	0.088	0.067	0.15	0.037	0.076
P-value of Enrolled + Enrolled*Ineligible	0.146	0.302	0.482	0.520	0.003
Mean of Dependent Variable, Control	0.719	0.582	0.042	0.299	0.261
Panel B: Number of Visits	(1)	(2)	(3)	(4)	(5)
Parent Enrolled	1.261**	0.336	0.564***	0.211	0.110
	(0.622)	(0.292)	(0.150)	(0.283)	(0.263)
Parent Enrolled*Ineligible Kid	−3.000***	−0.800	−0.519***	−0.354	−1.092***
	(1.028)	(0.519)	(0.148)	(0.446)	(0.385)
Ineligible Kid	0.689**	0.134	0.037	0.333**	0.192
	(0.342)	(0.170)	(0.050)	(0.134)	(0.134)
Observations	2996	2996	2996	2996	2996
R-squared	0.092	0.061	0.108	0.031	0.042
P-value of Enrolled + Enrolled*Ineligible	0.048	0.314	0.409	0.717	0.001
Mean of Dependent Variable, Control	3.097	1.337	0.117	0.773	0.604

Notes: The sample is all children aged 15 and under (N=2996).Children age 12-15 are considered "Ineligible" and children under 11 are considered "Eligible". Above regressions are estimated coefficients on "Parent Enrolled in Health Insurance" from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status Ineligible Kid*Parent Enrolled is instrumented with random assignment status*Ineligible kid.The dependent variable in panel A is whether or not the child has visited various providers over the past year. The dependent variable in panel B is the number of times the child has visited various providers over the past year. Regressions control for household size, household size squared,logged parental income, parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value. Robust standard errors in parentheses, clustered at the family level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.3: Effects of Parent Insurance on Out of Pocket Expenditures by Child Eligibility

	Any Provider	Pharmacy	EMP (Covered Provider)	Public Facilities	Private Facilities
Panel A: Ever Spend	(1)	(2)	(3)	(4)	(5)
Parent Enrolled	−0.048	−0.030	0.006	−0.012	−0.032
	(0.079)	(0.081)	(0.004)	(0.009)	(0.073)
Parent Enrolled*Ineligible Kid	−0.115	−0.132	−0.006	0.014	−0.297**
	(0.148)	(0.149)	(0.004)	(0.010)	(0.117)
Ineligible Kid	0.004	−0.003	0.001	−0.002	0.045
	(0.048)	(0.049)	(0.001)	(0.001)	(0.038)
Observations	2996	2996	2996	2996	2996
R-squared	0.07	0.066	0.009	0.001	0.075
P-value of Enrolled + Enrolled*Ineligible	0.242	0.244	0.817	0.328	0.001
Mean of Dependent Variable, Control	0.597	0.573	0.000	0.004	0.259
Panel B: Ln(Amount Spent	(1)	(2)	(3)	(4)	(5)
Parent Enrolled	−0.364	−0.201	0.027	−0.018	−0.266
	(0.480)	(0.468)	(0.019)	(0.030)	(0.390)
Parent Enrolled*Ineligible Kid	−1.177	−1.048	−0.026	0.022	−1.653***
	(0.872)	(0.833)	(0.018)	(0.032)	(0.633)
Ineligible Kid	0.268	0.216	0.005	−0.007	0.264
	(0.289)	(0.277)	(0.005)	(0.005)	(0.207)
Observations	2996	2996	2996	2996	2996
R-squared	0.096	0.093	0.009	0.005	0.082
P-value of Enrolled + Enrolled*Ineligible	0.056	0.104	0.817	0.403	0.000
Mean of Dependent Variable, Control	3.450	3.192	0.000	0.009	1.361

Notes: The sample is all children aged 15 and under (N=2996).Children age 12-15 are considered "Ineligible" and children under 11 are considered "Eligible". Above regressions are estimated coefficients on "Parent Enrolled in Health Insurance" from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status Ineligible Kid*Parent Enrolled is instrumented with random assignment status*eligible kid.The dependent variable in panel A is whether or not the child had any health expenditures at various providers over the past year. The dependent variable in panel B is the ln(healht expenditures +1) at various providers over the past year. Regressions control for household size, household size squared,logged parental income, parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value. Robust standard errors in parentheses, clustered at the family level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.4: Effects of Parent Insurance on Health Indicators by Child Eligibility

	Ever Sick	Checkup	Forgone Treatment	Times Sick	Days of School Missed	Cold and Flu
Panel A: Ever Spend	(1)	(2)	(3)	(4)	(5)	(6)
Parent Enrolled	0.015	−0.040	−0.054	0.676**	3.233	0.011
	(0.064)	(0.071)	(0.055)	(0.336)	(2.003)	(0.074)
Parent Enrolled*Ineligible	−0.192	−0.009	−0.106	−1.739***	−4.872**	0.029
	(0.144)	(0.111)	(0.093)	(0.613)	(2.394)	(0.139)
Ineligible	0.062	0.028	0.005	0.455**	−0.144	0.016
	(0.048)	(0.034)	(0.029)	(0.215)	(0.673)	(0.046)
Observations	2996	2996	2996	2996	2996	
R-squared	0.09	0.045	0.019	0.079	0.011	0.019
P-value of Enrolled + Enrolled*Ineligible	0.198	0.641	0.071	0.053	0.212	0.748
Mean of Dependent Variable, Control	0.729	0.193	0.116	1.826	2.274	0.334

Notes: The sample is all children aged 15 and under (N=2996) except for column 3 which includes children between ages 5 and 15. For days of school missed, this question was only asked of children 5 and older. Children age 12-15 are considered "Ineligible" and children under 11 are considered "Eligible". Above regressions are estimated coefficients on "Parent Enrolled in Health Insurance" from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status Ineligible Kid*Parent Enrolled is instrumented with random assignment status*eligible kid. The dependent variable are various measures of health status: whether the child had ever been sick in the past year; the number of times sick; the number of days of school missed due to illness. Regressions control for household size, household size squared,logged parental income, parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value. Robust standard errors in parentheses, clustered at the family level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.5: Effects of Health Insurance for Eligible children with/out an Ineligible Sibling

	Any Provider	Pharmacy	EMP (Covered Provider)	Public Facilities	Private Facilities	Sick
Panel A: Ever Visit/Sick	(1)	(2)	(3)	(4)	(5)	(6)
Enrolled Parent	0.014	0.004	0.222***	0.067	0.006	0.016
	(0.065)	(0.082)	(0.052)	(0.084)	(0.081)	(0.064)
Ineligible Sibling*Enrolled Parent	−0.009	0.075	0.023	−0.017	−0.066	0.010
	(0.200)	(0.233)	(0.113)	(0.211)	(0.195)	(0.197)
Ineligible Sibling	−0.039	−0.059	0.004	−0.018	0.006	−0.030
	(0.038)	(0.046)	(0.019)	(0.042)	(0.039)	(0.038)
Observations	2172	2172	2172	2172	2172	2172
R-squared	0.073	0.061	0.144	0.04	0.075	0.072
P-value of Enrolled + Enrolled*Ineligible	0.981	0.716	0.016	0.796	0.733	0.888
Mean of Dependent Variable, Control Group	0.763	0.618	0.054	0.308	0.285	0.772
Panel B: Number of Visits/Times Sick	(1)	(2)	(3)	(4)	(5)	(6)
Enrolled Parent	1.905***	0.530*	0.633***	0.417	0.257	1.020***
	(0.686)	(0.315)	(0.172)	(0.306)	(0.311)	(0.360)
Ineligible Sibling*Enrolled Parent	−3.201*	−0.944	−0.349	−0.983	−0.768	−1.689*
	(1.689)	(0.812)	(0.334)	(0.779)	(0.624)	(0.935)
Ineligible Sibling	0.444	0.114	0.042	0.199	0.097	0.305*
	(0.336)	(0.162)	(0.069)	(0.160)	(0.117)	(0.179)
Observations	2172	2172	2172	2172	2172	2172
R-squared	0.067	0.05	0.1	0.028	0.037	0.062
P-value of Enrolled + Enrolled*Ineligible	0.403	0.583	0.323	0.432	0.332	0.445
Mean of Dependent Variable, Control Group	3.357	1.43	0.156	0.809	0.664	1.939

Notes: The sample is eligible children aged 11 and under (N=2172). Above regressions are estimated coefficients on "Parent Enrolled in Health Insurance" from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status Older Sibling*Parent Enrolled is instrumented with random assignment status*older sibling. The "All eligible" category refers to children age 11 and under at baseline; "Older sibling" refers to children age 12 and older at baseline. The dependent variable in panel A is whether or not the child has visited various providers over the past year, or (Column 9) whether the child was ever sick in the past year. The dependent variable in panel B is the number of times the child has visited various providers over the past year, or (Column 9) the number of times the child was sick in the past year. Regressions control for household size, household size squared,logged parental income, parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value. Robust standard errors in parentheses, clustered at the family level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3.6: Effects of Health Insurance Among Ineligible children with/out an Ineligible Sibling

	Any Provider	Pharmacy	EMP (Covered Provider)	Public Facilities	Private Facilities	Sick
Panel A: Ever Visit/Sick	(1)	(2)	(3)	(4)	(5)	(6)
Enrolled Parent	−0.179	−0.035	−0.013	−0.163	−0.193	−0.204
	(0.171)	(0.175)	(0.043)	(0.153)	(0.138)	(0.171)
Eligible Sibling*Enrolled Parent	−0.059	−0.209	0.089	0.149	−0.184	0.018
	(0.267)	(0.272)	(0.061)	(0.241)	(0.194)	(0.266)
Eligible Sibling	−0.023	−0.005	−0.013	0.001	−0.041	−0.028
	(0.056)	(0.058)	(0.012)	(0.051)	(0.043)	(0.056)
Observations	824	824	824	824	824	824
R-squared	0.04	0.021	0.039	0.046	0.029	0.048
P-value of Insur + Insur*Youngersibs =0	0.248	0.243	0.067	0.941	0.006	0.364
Mean of Dependent Variable, Control	0.599	0.484	0.011	0.272	0.196	0.61
Panel B: Number of Visits/Times Sick	(1)	(2)	(3)	(4)	(5)	(6)
Enrolled Parent	−1.939	−0.306	−0.013	−0.618	−0.952**	−1.412*
	(1.274)	(0.665)	(0.064)	(0.504)	(0.458)	(0.811)
Eligible Sibling*Enrolled Parent	0.540	−0.265	0.1400.810	0.073	0.562	
	(1.710)	(0.912)	(0.091)	(0.743)	(0.538)	(1.056)
Eligible Sibling	−0.623	−0.173	−0.016	−0.135	−0.225	−0.384
	(0.388)	(0.195)	(0.016)	(0.157)	(0.150)	(0.243)
Observations	824	824	824	824	824	824
R-squared	0.008	0.018	0.031	0.012	−0.008	0.003
P-value of Insur + Insur*Youngersibs=0	0.222	0.36	0.049	0.737	0.005	0.238
Mean of Dependent Variable, Control	2.387	1.084	0.013	0.675	0.442	1.516

Notes: The sample is eligible children aged 12 and over (N=824). Above regressions are estimated coefficients on "Parent Enrolled in Health Insurance" from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status and Younger Sibling*Parent Enrolled is instrumented with random assignment status*younger sibling. The dependent variable in panel A is whether or not the child has visited various providers over the past year. The dependent variable in panel B is the number of times the child has visited various providers over the past year. Regressions control for household size, household size squared,logged parental income, parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value. Robust standard errors in parentheses, clustered at the family level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3A.1: Baseline Characteristics of Children by Age Group

Variables	Age 0 -5 Mean	Difference (C-T)	Difference P-Value	Age 6 -11 Mean	Difference (C-T)	Difference P-Value	Age 12 -15 Mean	Difference (C-T)	Difference P-Value
Panel A: Ever Visit/Sick	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	2.81	−0.13	0.18	8.36	−0.06	0.47	13.23	−0.03	0.64
Female	0.480	−0.031	0.340	0.473	0.011	0.700	0.504	−0.060	0.099
Ever sick	0.859	−0.001	0.951	0.752	0.027	0.304	0.672	0.011	0.855
Number of times sick	2.838	0.080	0.757	1.972	−0.100	0.486	1.691	0.069	0.639
Forgone treatment	0.197	−0.045	0.140	0.183	−0.029	0.273	0.165	0.010	0.835
Ever visit health provider	0.854	−0.010	0.677	0.741	0.028	0.302	0.665	0.014	0.699
Total number of visits, all providers	5.157	−0.181	0.689	3.469	−0.148	0.648	2.858	−0.026	0.845
Total health expenditures	869.31	204.72	0.33	448.80	75.90	0.17	417.63	27.85	0.85
Children (N)	919	−−	−−	1253	−−	−−	824	−−	−−

Notes: Above are sample averages of selected variables by age groups of children at baseline. Columns 1,4, and 7 show averages for all children within the age category; Columns 2,5,and 8 show the difference in average characteristics between children in the Control group and children in the Treatment group; Columns 3,6, and 9 show the p-value of the difference. Health providers consist of EMPs, public clinics, pharmacies, private hospitals, private doctors, public hospitals, and laboratory visits. All health and visit variables are reported to be during the past year. All income and expenditure data are in 2008 Cordobas. Children who were not sick in the past year are included as zeros for number of times sick and all visit/spending variables. Forgone treatment in past year due to lack of money was calculated to be zero for children who were not sick in the past year.$***p < 0.01, **p < 0.05, *p < 0.1$

Table 3A.2: Predictors of Health Insurance Enrollment

	All Children	All Adults	Parents
Panel A: Ever Visit/Sick	(1)	(2)	(3)
6 Month Subsidy	0.309***	0.372***	0.359***
	(0.021)	(0.016)	(0.023)
Ineligible Child	0.002	−0.012	−0.014
	(0.029)	(0.011)	(0.015)
6 Month Subsidy*Ineligible Child	−0.046*	−0.089***	−0.076**
	(0.028)	(0.029)	(0.034)
Household Size	−0.018**	0.007	−0.009
	(0.008)	(0.007)	(0.009)
Household Size Squared	0.000	−0.001**	0.000
	(0.000)	(0.000)	(0.000)
Age	−0.001	−0.001	−0.002
	(0.007)	(0.006)	(0.008)
Age-Squared	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)
Female	−0.006	0.024	0.007
	(0.012)	(0.015)	(0.019)
Parent's Years of Education	0.003	0.001	0.001
	(0.002)	(0.002)	(0.002)
Ln(Parent's Income)	0.009	0.021***	0.015
	(0.008)	(0.008)	(0.010)
Ever Sick in Past Year	0.022	0.010	−0.002
	(0.017)	(0.018)	(0.022)
Forgone Treatment	0.072***	0.053***	0.081***
	(0.025)	(0.018)	(0.023)
Constant	−0.046	−0.178	−0.049
	(0.085)	(0.115)	(0.161)
R-squared	0.190	0.2263	0.2163
Observations	2996	2608	1614
Round and Market Fixed Effects?	Y	Y	Y

Notes: Sample in column 1 is all children age 15 and under at baseline; sample in column 2 is all adults; sample in column 3 is all parents with at least one child aged 15 years and under . Above are coefficients from OLS regressions of whether or not the child's parent enrolled in health insurance on baseline variables, conditional on random assignment status. All regressions include market and round fixed effects. Missing income values are imputed to the mean, and an indicator variable is included in the regression. Robust standard errors are clustered at the family level. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 3A.3: Where Sought Treatment For Last Illness

	Public Facility	Private Facility	EMP	Pharmacy
	(1)	(2)	(3)	(4)
Parent Enrolled	−0.013	0.007	0.152***	−0.074
	(0.088)	(0.086)	(0.047)	(0.066)
Parent Enrolled*Ineligible	−0.009	−0.295*	−0.142**	0.477***
	(0.184)	(0.163)	(0.065)	(0.174)
Ineligible	0.028	−0.050	−0.031**	0.038
	(0.040)	(0.036)	(0.014)	(0.033)
Observations	2164	2164	2164	2164
R-squared	0.001	0.001	0.064	−0.011
P-value of Enrolled + Enrolled*Ineligible	0.904	0.058	0.846	0.019
Mean of Dependent Variable, Control	0.382	0.326	0.0482	0.196

Notes:The sample is all children aged 15 and under who were sick in the past year at follow=up (N=2996) .Children age 12-15 are considered "Ineligible" and children under 11 are considered "Eligible". Above regressions are estimated coefficients on "Parent Enrolled in Health Insurance" from 2SLS-IV estimates where "Parent Enrolled in Health Insurance" is instrumented with random assignment status; Ineligible Kid*Parent Enrolled is instrumented with random assignment status*Ineligible kid. The dependent variable in all regressions is a dummy variable indicating where the child sought treatment for the last illness. Regressions control for household size, household size squared,logged parental income, parent's years of education, age of child, age of child squared, gender, whether the child was sick in the past year, the number of times sick, total number of health visits, and survey round and market fixed effects. Individuals without valid income data were imputed to be the median and regressions were run with a dummy variable indicating the missing value. Robust standard errors in parentheses, clustered at the family level.$***p < 0.01, **p < 0.05, *p < 0.1$

Table 3A.4: Moral Hazard

	Consult Doctor Immediately	Keep Child Home From School	Restrict time they leave home	Restrict Certain Foods	Home Remedies	Sum
	(1)	(2)	(3)	(4)	(5)	(6)
Parent Enrolled	−0.057	−0.203	0.197	−0.344	−0.468	−0.875
	(0.255)	(0.470)	(0.497)	(0.462)	(0.465)	(1.408)
Enrolled* Have Ineligible Kid	−0.063	−0.748	−1.116	−0.055	0.793	−1.189
	(0.473)	(0.802)	(0.855)	(0.770)	(0.797)	(2.419)
Have Ineligible Kid	−0.106	−0.007	0.120	0.007	−0.165	−0.150
	(0.114)	(0.202)	(0.214)	(0.199)	(0.205)	(0.621)
Constant	5.668***	3.003**	3.230**	1.805	1.691	15.396***
	(0.740)	(1.408)	(1.480)	(1.336)	(1.331)	(4.147)
Observations	1460	1460	1460	1460	1460	1460
R-squared	0.013	0.021	0.008	0.014	0.017	0.016
P-value of Insur and Insur*Have Ineligible Kid	0.765	0.146	0.189	0.520	0.617	0.298
Mean of Dependent Variable, Control	5.158	4.250	3.866	2.404	2.111	17.790

Notes: Sample is parent respondents with at least one child age 5-11 at baseline (N=1460). Above are coefficient estimates from 2SLS regressions of enrolling in health insurance on a moral hazard index, where the we instrument insurance enrollment with the randomly assigned subsidy (TOT). This index was constructed from a series of questions where the parents were asked: "Please indicate whether you would do any of 5 behaviors (keep the child home from school, consult a doctor Immediately,restrict the amount of time they leave the house or bed, restrict certain foods, or give home remedies) to prevent your children from illness/injury under each of the circumstances below: 1) child has trouble breathing; 2) child has a sore throat; 3) child is excessively tired or fatigued; 4) child has a higher than normal fever; 5) child has stomach problems or diarrhea; 6) child has a minor cut on their leg; 7) child has a swollen ankle. For each of the 6 circumstances, responses were summed (1=Yes, 0=No) as a summary of number actions that would be taken. Therefore, for each column 1-5 the dependent variable potentially ranges from 0 to 6. Column 6 aggregates all responses and therefore potentially ranges from 0 to 30. All regressions include market and round fixed effects. Robust standard errors in parentheses.$***p < 0.01, **p < 0.05, *p < 0.1$

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