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Summary

Antibiotics and vaccines are undoubtedly among the greatest milestone discoveries in human history. They are key tools in the fight against infectious diseases that continue to burden the health sector in developing countries. Infectious diseases are not only responsible for the disproportionate share in mortality in low- and middle-income countries, but also impose a huge economic burden on the poor. The introduction of antibiotics and vaccines has revolutionized modern medicine by arming healthcare workers with prevention and curative tools across a wide spectrum of infectious diseases. However, the appropriate use of both antibiotics and vaccines has been a subject of scrutiny and debate within the health and development literature. Indeed, while antibiotics are misused and overused, vaccines – which have the potential to reduce the need for antibiotics – are underutilized. Recent decades have witnessed a rise in antibiotic resistance attributed to burgeoning antibiotic consumption along with failures in implementing antibiotic stewardship in healthcare settings. Studies have shown that regulatory and socioeconomic environments in developing countries encourage the unregulated and indiscriminate use of antibiotics.

In this thesis, we propose a novel approach to tackle the unjustified sale of antibiotics in community pharmacies. The *first chapter* sets out the results of a field experiment aimed at reducing the non-prescription sale of antibiotics in the developing world. Using a randomized controlled trial in Ethiopia, in collaboration with the Addis Ababa Food Medicine Health Care Administration and Control Authority (AAFMHACA), we examine the effectiveness of three types of nudges – namely, a coercive letter, a moral appeal letter, and an informational sticker with evocative messages placed in pharmacies – in reducing over-the-counter sales of antibiotics. The results of an audit study, conducted two to three weeks after the intervention, indicate that all three inexpensive nudges lead to a significant decrease in the sale of antibiotics without prescription, compared to the control (untreated) group of pharmacies. The coercive letter has the highest impact (reducing over-the-counter sales of antibiotics by 23.4 percent compared to the control group), followed by the appeal letter and the sticker treatment (with a reduction of 16.5 and 13.5 percent compared to the control, respectively). These findings suggest that antibiotic misuse can be curtailed by adapting simple and low-cost behaviorally informed rules to regulate community pharmacies, at least in the short run.

The *second chapter* is a sequel to the first and reports on the persistent and heterogeneous effects of the treatments five months after the intervention. The results show that our treatments

persisted well into the fifth month, despite some waning of the effects. The heterogeneity analysis indicates that the findings are robust across different subgroups of characteristics.

The *third chapter* assesses the determinants of inequities in child immunization status. One approach to reducing excessive antibiotic use is through investing resources in protection strategies that reduce the need for antibiotic prescription in the first place. One strategy is the wider use of vaccines in the population particularly through childhood immunization programs. Childhood vaccination is deemed a global intervention aimed at improving child survival and health. It reduces the economic burden on households by reducing the proportion of households facing catastrophic payments from out-of-pocket health expenses. Tragically, not all children of similar age have the benefit of vaccines as the odds of getting immunized largely depend on several socioeconomic factors. In the last chapter of the thesis, we quantify and study the determinants and decomposition of immunization inequality in Ethiopia using two rounds of Demographic and Health Survey (DHS) data. The determinants of immunization are analyzed based on the circumstances of the child, household, community, and region-specific characteristics in a multinomial logit specification to account for the degree of immunization. The study employs the methodology in Barros et al. (2009) to estimate the Human Opportunity Index (HOI) and Dissimilarity Index(D-index) and thus assess changes between the two periods. Furthermore, we employ the Shapley decomposition to measure the role and the contribution of circumstances to inequality.

Our study reveals that between 2011 and 2016 the overall coverage rate for Ethiopia increased with significant regional variations. The important predictors of complete immunization are delivery to a health facility, maternal primary education, mother practicing Christianity, and whether distance to the nearest health facility is considered a problem. We find that while the HOI increased from 18 percent to 28.1 percent, the inequality index only showed a marginal improvement, declining a meagre 2 percent. These improvements are largely appropriated by the urban population as inequality was constant in rural areas over the study period. The decomposition reveals that regional variations, distance to health facilities, religious affiliation, household economic status and maternal education consistently contribute to inequality.

Chapter One

Nudging the Pharmacist to Combat the Non-Prescription Sale of Antibiotics

> The time may come when penicillin can be bought by anyone in the shops. Then there is the danger that the ignorant man may easily under-dose himself and by exposing his microbes to nonlethal quantities of the drug make them resistant.
>
> -Alexander Fleming, 1945, p.93

1.1 Introduction

The ease of acquiring drugs such as antimicrobials from community pharmacies without a prescription is a threat to the control of irrational antimicrobial consumption and is associated with increasing antibiotic resistance. Antibiotic resistance occurs when pathogens like bacteria develop the ability to defeat the very drugs designed to kill them. One of the greatest discoveries of modern medicine, antibiotics have become the mainstream infrastructure in human and animal health. Unfortunately, antibiotics suffer from transmissible loss of efficacy over time and scientists have warned of a "post-antibiotic era" in which common infections and minor injuries can once again kill (Spellberg et al., 2016), thereby undoing decades of progress in decreasing morbidity and mortality from infectious diseases (Alsan et al., 2015).

Since antibiotic resistance makes it harder and expensive to treat infections and control epidemics, the phenomenon has mushroomed into an economic problem.[1] O'Neil (2016) points out that deaths attributable to antibiotic resistance may exceed 10 million per year, costing the global economy a massive US $60–$100 trillion in economic output and loss of human capital. At the individual level, antibiotic resistance results in lengthier illness and loss of productive days. Using data for 2002–2014 from the Medical Expenditure Panel Survey–Household Component, Thorpe et al. (2018) estimate that, in the US, antibiotic resistance added $1,383 to the cost of treating a patient with a bacterial infection. As emphasized by, e.g., Byarugaba (2004) and Ahmad & Khan (2019), the problem is particularly severe in developing countries

[1] The Berlin Declaration of the G20 Health Ministers, issued in 2017, acknowledges the severe impact of "global health risks, such as infectious disease outbreaks and antimicrobial resistance" on the global economy (see https://carb-x.org/wp-content/uploads/2018/02/2017_02_03_G20_Health_Ministers_Declaration_engl.pdf).

where it increases the risk of the medical poverty trap. All in all, there is a growing awareness that, if unaddressed, antimicrobial resistance can hamper countries' human capital and is likely to impede progress towards the 2030 Sustainable Development Goals (World Bank, 2019).

Antibiotic resistance is, to some extent, a natural phenomenon, but its increasing pace has been ascribed to the upward trend in antibiotic consumption[2] (Bronzwaer et al., 2002; Aslam et al., 2018) and to antibiotic misuse (Malik & Bhattacharyya, 2019;). Recent evidence (Adda, 2020) indicates that although antibiotics are mainly used in animal farming antibiotic resistance is largely due to the prescriptions of antibiotics for humans and is particularly sensitive to the use of the newest drugs. In a study involving 76 countries around the world, Klein et al. (2018) find that the defined daily doses of human antibiotic consumption increased by 65 percent between 2000 and 2015, primarily driven by an increase in consumption within low- and middle-income countries. The current Coronavirus pandemic may drive antibiotic resistance due to a compromise in stewardship activities and a general increase in hospital admissions and infections.

Radical and concerted efforts to tackle the problem of antibiotic resistance should include encouraging the invention of new drugs as well as the sustainable and judicious use of the currently available medicines. Although the problem of antibiotic resistance is increasingly being documented as a behavioral and social – as opposed to just a medical – problem (Rönnerstrand & Lapuente, 2017), interventions to preserve the effectiveness of antimicrobials have focused on inappropriate prescriptions by healthcare providers in clinical settings (Meeker et al., 2014; Garau, 2006; Erku & Aberra, 2019), thereby missing the use of non-prescribed antibiotics (Morgan et al., 2011), also called 'over-the-counter' (OTC) antibiotics. This is despite the evidence that 50 percent of antibiotics worldwide are obtained without a prescription and that community pharmacies are a major source of non-prescribed antibiotics (Cars & Nordberg, 2005). In a random-effects meta-analysis of 38 studies from 24 countries, Auta et al. (2019) find that, in community pharmacies, 62 percent of antibiotics are sold without a prescription; 78 percent are supplied following a patient request and 52 percent based on a

[2] See the WHO Report on Antimicrobial resistance and primary healthcare (2018) available at https://apps.who.int/iris/bitstream/handle/10665/326454/WHO-HIS-SDS-2018.56-eng.pdf

pharmacist's recommendation (similar findings are reported in Van Boeckel et al., 2014; Kalungia et al., 2016; Chang et al., 2019).

Antibiotic use acts as a common good with positive and negative externalities (e.g., Eggleston et al., 2010; Giubilini, 2019).[3] Positive externalities arise because antibiotic use curtails infection and protects society. Negative externalities occur due to antibiotic resistance, which has an undesirable effect on people other than the immediate users: every individual's consumption of antibiotics affects the ability of every other person to use the same antibiotics. Even in the case of therapeutically justified antibiotic use, the benefits are borne by the individual, but the costs - in terms of resistance - are socialized.

To improve the appropriate use of antibiotics, the recommendation from many studies is to enforce measures that promote access to antibiotics only with a prescription (hence following the necessary diagnosis), especially in countries where OTC sales of antibiotics are very common (e.g., Kalungia et al., 2016; Chen et al., 2018; Tangcharoensathien et al., 2018; Ahmad & Khan, 2019; Chen et al., 2020).[4] Evidence of the impact of interventions that limit the non-prescription sale of antibiotics remains, however, scant (Grigoryan et al., 2019) and the existing studies are of limited generalizability due to differences in methods and outcome measures (Jacobs et al., 2019).

Against this backdrop, and with the help of the Addis Ababa Food Medicine Health Care Administration and Control Authority (AAFMHACA), we conducted a field experiment to test the effectiveness of a set of behavioral interventions in reducing the sale of OTC antibiotics. We implemented a randomized controlled trial in Addis Ababa, the capital city of Ethiopia, where previous studies have estimated a remarkably high prevalence of OTC antibiotics of above 60 percent (Gebretekle & Serbessa, 2016; Auta et al., 2019).

We experimented with three types of behavioral nudges explicitly designed to increase adherence to dispensing antibiotics only to customers with prescriptions. In the absence of

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[3] Common goods, or common pool resources, are goods for which rivalry exists (the use of the good by someone reduces the possibility of others using it), but exclusion is not possible. A famous example, provided by Hardin (1968), is that of a pasture available to many herdsmen.

[4] See also the 2019 WHO report available at https://apps.who.int/iris/bitstream/handle/10665/312306/9789289054089-eng.pdf

adequate resources for technology-based registration of medicines and with a weak regulation enforcement capacity, behavioral interventions adapting existing systems can be employed relatively quickly and at a low cost. Specifically, we hand-delivered a coercive letter, a moral appeal (or persuasion) letter, and a sticker to be placed on the pharmacy wall.

The letters had a similar introduction and informed pharmacists about the costs of irrational antibiotic dispensing and consumption in the Ethiopian context. The coercive letter took the form of a warning and pointed out the legal consequences of selling OTC antibiotics. The letter explained that the authorities randomly audit pharmacies and, in case of misconduct, possible sanctions include revoking a professional license and/or pharmacy closure. The moral appeal letter was meant to encourage the pharmacists to engage in good dispensing behavior given their unique position in the health system. The letter appealed to the pharmacist's key role within the community and stressed the importance of advising the patients requesting antibiotics without a prescription to visit the nearest health center, rather than selling the drug. It has been suggested that pharmacists in developing countries value their professional role and status (see, e.g., Laing et al., 2001) and that the inappropriate use of antibiotics by professionals can be reduced with education (e.g., Tangcharoensathien et al., 2018). Both types of letters bore the letterhead and logo of AAFMHACA and were signed by the head of health facilities and the professional inspection process.

Since the letters were provided once and might fail to remain salient over time, the third treatment was to place and display an inexpensive sticker inside the pharmacy. The sticker included a statement forbidding OTC antibiotics, bore the logo of AAFMHACA, and was placed on the pharmacy walls by personnel from AAFMHACA.

To evaluate outcomes, we employed simulated (or standardized) patients (SPs) who were well trained to present the symptoms of two health conditions – Upper Respiratory Tract Infection (URTI) and Urinary Tract Infection (UTI) – to multiple pharmacists. The URTI case mimicked pneumonia in a child who was not present on site. The UTI case involved female patients and was further divided into product-based requests and symptom-based requests to investigate whether describing the symptoms, rather than asking for a specific antibiotic, influences the assessment of the customer's needs by a pharmacist with patient-regarding preferences. The description of the symptoms may, for instance, render needs more salient or make them seem more urgent. The SPs employed in the study made unannounced visits to close to 800

pharmacies. Immediately after exiting the pharmacy, they recorded details of their interactions with the pharmacists (e.g., price if sold and advice if any) as well as the pharmacist's demographic details (such as gender and perceived age).[5] Since antibiotics are in different classes according to cautious order of use (see WHO AWaRe-Essential meds), the study sheds light on the willingness to prescribe and dispense different classes of antibiotics. In addition, we observed the prices charged if an antibiotic was offered, which allows us to explore whether and how prices correlate with the intervention and the pharmacists' demographics.

Previous research argues in favor of the use of SPs when the risks to and burdens on the people under scrutiny are minimal compared to the benefits and valuable knowledge gained by society (Rhodes & Miller, 2012).[6] We suggest that our experiment meets this requirement for three reasons. First, selling OTC antibiotics is the norm in Ethiopia and thus our SPs would cause minor psychological harm to the pharmacists when asking for a cure. Second, the SPs were told not to push the request for antibiotics, but to accept the pharmacist's decision. Finally, finding an effective intervention to curb antibiotic misuse will have extremely important implications for the global economy and healthcare in general, particularly for developing countries.

The results from a probit regression controlling for patient fixed effects and observable pharmacist characteristics indicate that all three interventions resulted in a decline in the sale of OTC antibiotics. Pharmacists in the coercive and moral appeal treatment groups sold, respectively, 24.3 percent and 16.5 percent less than their counterparts in the control (untreated) group. The informational sticker treatment led to a decline of approximately 13.5 percentage points in non-prescribed antibiotics.

This study contributes to the literature in five ways. First, it adds evidence to the growing literature on improving adherence to good practices via inexpensive interventions (see, e.g., Habyarimana & Jack, 2011; Goldzahl et al., 2018; Ahomäki et al., 2020). Behavioral nudges can indeed be important tools to ensure that antibiotics are used only when appropriate. Second,

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[5] Commonly used in medical education, SPs are trained fake patients who present symptoms of an illness to health professionals. Further details on the SP methodology is provided in Section 4.3.

[6] Advantages of the SP method are also discussed by, among others, Das et al. (2016) and Collins et al. (2021).

our study contributes to the strand of literature that examines compliance with rules, particularly when enforcement is weak and sanctions are not severe (e.g., Sutter et al., 2020). Third, we provide a conceptual framework for how and why the decision to dispense OTC antibiotics is made. Fourth, our study is an example of successful and cost-effective collaboration between the government and academics that benefits both parties (see Sacarny et al., 2017). Such partnerships provide a win-win collaboration in which policymakers can access scientific expertise and academics have the chance to test their hypotheses via experiments. Finally, our paper provides estimates of the prevalence of OTC antibiotics in an urban setting of a developing country.

The remainder of the chapter proceeds as follows. Section 2 provides the context and background of OTC antibiotics in developing countries. Section 3 offers a conceptual framework for the decision to dispense OTC antibiotics. Section 4 describes the experimental design. Section 5 presents the results of our interventions and Section 6 concludes.

1.2 Context: Self-medication in developing countries

Self-medication is defined as the selection and use of non-prescribed medicines by individuals to treat self-recognized illnesses or symptoms (WHO, 1998, p. 3). If practiced appropriately, it has major benefits for consumers, such as self-reliance and decreased expense. From the healthcare system point of view, it translates into reduced pressure on healthcare professionals for minor complaints. However, inappropriate practice can have potential dangers such as incorrect self-diagnosis, incorrect dosage, dangerous drug-drug interactions, and/or risk of dependence and abuse. As emphasized by, e.g., Ho (2017), in the absence of proper diagnostic indications for antibiotics, pharmacists' risk under and overuse of antibiotics contributing to the proliferation of antibiotic-resistant pathogens. Jamhour et al. (2017) show that patients who receive antibiotics without a prescription are more likely to stop when symptoms improve compared to patients with a prescription. Past research, in general, points out that multi-resistant bacteria are most common in communities with the highest use of OTC antibiotics (Servia-Dopazo & Figueiras, 2018; Tangcharoensathien et al., 2018).

While many countries have clear guidelines on which drugs can and cannot be sold without a medical prescription, often these guidelines are not strictly followed either by consumers or drug dispensers. Antibiotics are a group of medicines that have become victims of this

malpractice. This has encouraged self-medication without a formal diagnosis and facilitated the accumulation of 'leftover' antibiotics that may be used to treat future illnesses, thus resulting in a vicious cycle.

According to Morgan et al. (2011), except for North Europe and North America, where antibiotics are largely restricted to prescription-only use, non-prescription access to antibiotics is common in the rest of the world. Even in industrialized countries like the United States, several studies indicate considerable use of leftover drugs obtained from a family member, a pharmacy, or a source outside the country (Grigoryan et al., 2006). The practice of self-medication with antibiotics is thought to be considerable in southern European countries. Lescure et al. (2018), for instance, estimate that patients who self-medicate with antibiotics are 20% in Greece, 16% in Romania, and 14% in Cyprus, whereas northern European countries like Sweden report rates of OTC self-medication as low as 2 percent.

Although self-medication with antibiotics – and consequent antibiotic misuse – is a current global problem, it is especially serious in developing countries like Ethiopia, where antibiotics are easily obtained over the counter (e.g., Gebretekle & Serbessa, 2016; Auta et al., 2019) and function as a 'quick fix' infrastructure put in place to rectify inefficiencies and cracks in the basic infrastructures of healthcare, water, and sanitation (Willis & Chandler, 2019). A recent World Bank (2019) report points out that, in most low- and middle-income countries, antibiotics have largely been used as a substitute for good quality public health systems. Ensuring access to prescription-only antibiotics requires not only a well-functioning health system, but also adequate law enforcement resources like effective registration systems for medicines and sufficient inspection capacity, which are largely absent in many poor countries.

As highlighted by Okeke (2010) and Alsan et al. (2015), the severity of the problem of antibiotic misuse in developing countries can be attributed to several factors. First, people living in low- and middle-income countries are more exposed to infectious diseases than people living in high-income countries and thus may be in more need of antibiotic therapy (both prescribed and non-prescribed).

Second, poverty contributes to a vicious cycle of need for antibiotics as the poor often engage in suboptimal antibiotic usage in the form of drug sharing, shorter than warranted courses of treatment, and in general poor-quality drugs matching their pockets. The pressure to take care

of urgent tasks and the so-called "scarcity mindset" (namely the perception of having too little of something; see, e.g., Shah et al., 2012; Mani et al., 2013) can make poor people myopic, overvaluing immediate (feeling better now) at the expense of future benefits (a visit to a doctor).

Third, access to medical doctors is limited and/or costly in developing countries, thus leading individuals to self-medicate or to view pharmacists as the easiest and cheapest medical option.[7] Studies have documented those pharmacies in developing countries are not only sites where medicines are bought and sold, but also prominent places where information and advice on health problems and treatments are sought and received (Goel et al., 1996; Kamat & Nichter, 1998). As emphasized by Ayukekbong et al. (2017), community pharmacies especially in Africa have emerged as the first level of healthcare, often providing unauthorized services like consultation and diagnosis.

Given the fact that pharmacists are important members of the healthcare system of developing countries and play a major role in medicine use, the next section seeks to discover the motivations governing the dispensing behavior of pharmacists.

1.3 Mechanisms governing the pharmacist decision to provide OTC antibiotics

We propose a conceptual framework that draws from research in the fields of social sciences, medicine, and health. We do not intend to provide a structural model, but rather an intuitive explanation of some of the mechanisms that govern the pharmacists' OTC sales. Our basic tenet is that community pharmacies in developing countries are not only health support locations providing medication, counselling, and advice to their customers, but also commercial entities acting in the pursuit of their own profits. Hence, the pharmacist sits at the junction of health and business services and the choice of selling OTC antibiotics is determined by a combination of the pharmacist's desire to cure the patient and his commercial interests.

[7] Research carried out in Maputo, Mozambique, by Rodrigues (2020) confirms the well-known problem of lack of good communication between medical doctors and patients in developing countries since many study participants tended to see their doctors briefly and to regard them as authoritarian, therefore opening the door to consultations with pharmacists.

Starting from the latter motivating factor, harmful OTC dispensing may occur because pharmacists pursue their own economic incentives, which reward the volume of medicines sold (Goel et al. 1996; Gebretekle & Serbessa, 2016). For this to be true, pharmacists – similarly to tax evaders (Allingham & Sandmo, 1972) and over-prescribing doctors (Sacarny et al., 2017) – must perceive the probability of detection and/or the penalties conditional on detection as low. Gebretekle & Serbessa (2016) find that pharmacists in Addis Ababa are well aware that the non-prescription sale of antibiotics is illegal and unethical. Yet, as they expect weak regulatory enforcement, it is in their best interest to sell as many drugs as possible. Regulatory bodies in developing countries like Ethiopia audit a few pharmacies periodically, but enforcement of the law in cases of detection is weak and often 'bypassable' through bribes (see, e.g., Pearson et al. 2018, pp. 24-25).[8] Changing the pharmacists' perception of incentives – specifically the probability of detection and penalties conditional on detection (an approach used in field experiments on tax compliance; see Fellner et al., 2013; Castro & Scartascini, 2015) – may reduce OTC dispensing.

Although monetary incentives are a key driver of non-prescription sales of antibiotics, previous studies in both developing and developed countries have shown that other factors can affect a pharmacist's willingness to dispense antibiotics without prescription (for reviews see Servia-Dopazo & Figueiras, 2018 as well as Jacobs et al., 2019). Unlike other healthcare professionals who are either not physically part of the community that they serve or are socially distant from the customers, pharmacists are often well integrated into the society. This may motivate them to develop an image as a health – rather than medicine – provider (Goel et al., 1996). Taking a pro-patient perspective, they may fail to understand their own prescribing skills and believe that they possess the knowledge to diagnose and treat infections (Alhomoud et al., 2018). When deciding to sell OTC antibiotics, pharmacists may either not perceive or underestimate the true costs of their actions. In this case, pharmacists are short-sighted as they value the short-

[8] Exacerbating the malpractice of OTC sales for financial reasons is the fear of losing customers, especially regular ones: if a pharmacist does not dispense OTC antibiotics, he believes that the customers can easily get them from any nearby pharmacy (e.g., Miller & Goodman, 2016). This kind of "bandwagon effect" has been documented by, e.g., Gebretekle & Serbessa (2016) in Addis Ababa and by Al-Mohamadi et al. (2013) in Jeddah, Saudi Arabia. Note that the bandwagon effect may be a motive for selling OTC antibiotics on its own: if it is widely believed that all pharmacies dispense antibiotics without prescription, then following this behavior may be acceptable because of, e.g., social pressure or replacement excuse (Bartling & Özdemir, 2017).

run benefits of the antibiotic to the customer above and beyond the long-run costs for both the individual and society.

The problem is particularly acute in low- and middle-income countries where there is a shortage of qualified pharmacists in community pharmacies. This is often attributed to the low remuneration of the profession, which leads competent and skilled pharmacists to look for jobs in the pharmaceutical industry (Sakeena et al., 2018). Although the existing legislation requires the presence of a qualified pharmacist at the community pharmacy during opening hours, the situation is not constantly monitored by the government authorities. Thus, in many cases, the dispensing of medicines (including antibiotics) is undertaken by non-pharmacist pharmacy-owners or other supporting persons, who do not have a proper medicine background and are not interested in appropriate professional development and training.[9] Most pharmacy staff members have an information deficit in antibiotic resistance and poor understanding of the problem.

When OTC antibiotic sales are due to the failure to understand one's own prescribing skills and/or unawareness of the benefits and harms of antibiotics, informing pharmacists about the side effects of irrational antibiotic consumption may make the costs of OTC antibiotics more salient and affect dispensing behavior.

There is evidence that customer pressure and the pharmacist's desire to meet customer demand are further driving forces behind OTC antibiotic sales in many low- and middle-income countries (e.g., Radyowijati & Haak, 2003; Gebretekle & Serbessa, 2016; Kho et al., 2017; Sakeena et al. 2018). Pharmacists frequently agree to sell OTC antibiotics on the insistence of customers, who often cannot afford to consult a medical doctor in developing countries and/or believe that consulting a physician is time-consuming. If pharmacists refuse, customers tend to react negatively. Additionally, as emphasized in the previous section, there is still confusion among customers about the pharmacist's role in developing countries: most customers believe that pharmacists are knowledgeable and can provide the proper medication. It is difficult for the pharmacists to refuse to dispense OTC antibiotics as they run the risk of being seen as

[9] As Goel et al. (1996) and, more recently, Sakeena et al. (2018) point out, the main source of educational training of pharmacy personnel in many developing countries appears to be pharmaceutical company salesmen.

incompetent and not up to their role (Kho et al., 2017). From this perspective, reducing the pressure and insistence of the customers and correcting their misperceptions about the pharmacist's role may make it easier for pharmacists to refuse to dispense OTC antibiotics.

1.4 Study design

The field study was carried out in Addis Ababa, in collaboration with AAFMHACA, between May and August 2019. It was preregistered on AsPredicted.org at the beginning of May 2019 (see https://aspredicted.org/blind.php?x=bv6fb9).

1.4.1 Study site

Addis Ababa is the capital and largest city of Ethiopia and the headquarters of the African Union. At the time of the study, the city was divided into ten boroughs, called sub-cities (see the map in Figure 1.1).[10] AAFMHACA is the main body that regulates the workings of community pharmacies, hospitals, and clinics in the city, but day-to-day operations of health facilities and healthcare providers are overseen by the sub-cities' health bureaus. Addis Ababa has an area of 540 square kilometers and the projected population size is approximately 3.5 million (Central Statistical Agency, 2011). Despite a 4 percent share in the total population, the city hosts 21 percent of the most important specialist hospitals in the country and nearly 43 percent of the total of medical doctors. Table 1.1 presents basic demographic and health-related data by Ethiopian region.

Addis Ababa has three types of community pharmacies or community drug retail outlets: pharmacies, drugstores/shops, and rural drug vendors. The difference in name reflects differences in the kind of medications they can dispense as well as the qualifications of the dispensers. Pharmacies are run only by holders of a university degree or above, drugstores by holders of a diploma in pharmacy, and rural drug vendors by health assistants.[11]

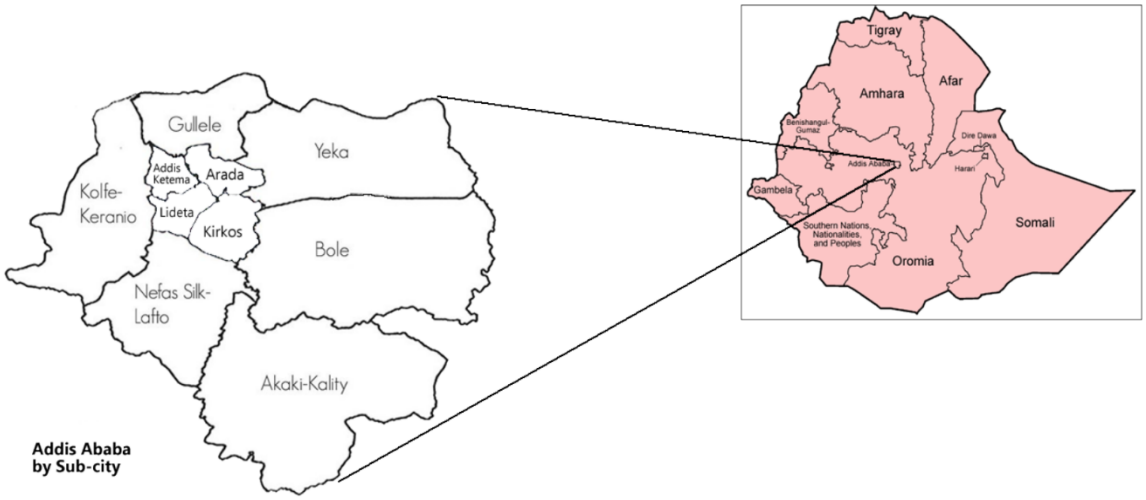
Even though Addis Ababa has better-quality health facilities than other parts of the country, recent simulated patient studies, such as Erku et al. (2016) and Koji et al. (2019), indicate that

[10] In October 2020, the Addis Ababa City Council established an eleventh sub-city.

[11] There is only one rural drug vendor in Addis Ababa, excluded from the study, which targets the highest-level community pharmacies, namely pharmacies and drug stores. We use the term 'pharmacy' to refer to both types of community pharmacies. Similarly, the term "pharmacist" refers not only to people who run a pharmacy, but also to those who run a drugstore.

a substantial number of community pharmacies in Addis Ababa sell OTC antibiotics. Erku et al. (2016) report that antibiotics were obtained 75.86% of the time for visits involving presentations of URTI symptoms and that requests for specific generic antibiotics were bestowed by more than two-thirds of the pharmacies visited. Koji et al. (2019) focus on pediatric illnesses and find that 63.4 percent of verbal antibiotic requests were dispensed.

Figure 1. 1 Addis Ababa sub-city map



Source: Office of the Mayor, Addis Ababa City Government; available at http://www.addisababa.gov.et/ar/web/guest/city-map

1.4.2 Experimental treatments

To overcome the problem of non-prescription dispensing of antibiotics and to account for the heterogeneity of motives that likely underlie the pharmacists' decision to sell OTC antibiotics, our experiment consists of three treatments or nudge-like interventions: (1) the delivery of a so-called moral appeal letter, (2) the delivery of a so-called coercive letter, and (3) the compulsory placement of a sticker within the pharmacy.

The letters and the message on the sticker were written in the local official working language, Amharic, and bore the letterhead, logo, and stamp of AAFMHACA. To reduce intention-to-treat bias and to dispel doubts about the reliability of the information (Webb and Sheeran, 2006), personnel from AAFMHACA hand-delivered the letters and placed the sticker in an appropriate location in the pharmacies.

Table 1. 1 Health profile in Addis Ababa and other Ethiopian regions

	Tigray	Afar	Amhara	Oromia	Somali	Benishangul Gumuz	SNNPR	Gambella	Harari	Addis Ababa	Dire Dawa	National
Percentage Distribution of Population	5.8	1.9	23.3	36.7	6	0.9	20.4	0.4	0.2	3.7	0.5	100
Birth deliveries by skilled attendant	65.5	37.2	68.2	74	31.5	53	78.3	31.3	113	124.7	71.3	71
Outpatient attendance per capita	1.8	0.4	1.1	0.5	0.2	0.8	0.6	0.7	1.3	1.7	1.3	0.8
Density of health officer per 10,000 population	0.9	0.6	0.8	0.9	0.4	1.98	0.9	2.5	1.1	3.5	1.4	0.97
Hospital to population ratio*	169258	302000	310809	521586	574900	533001	245,769	145333	123000	312182	233000	335334
Number of General Physicians & Specialists	189	163	614	957	183	60	618	22	62	502	57	
Share of health budget from total allocated budget	8.6	9.9	14.4	12.9	8.9	14.9	17.4	6.6	3.4	11.3	5.5	11.7

* "Hospital to population ratio" reflects the number of persons served by each hospital.

Source: Health and Health-Related Indicators 2017 (the Federal Democratic Republic of Ethiopia, Ministry of Health), available at: http://repository.iifphc.org/bitstream/handle/123456789/395/Health%20and%20Health%20Related%20Indicator%202017.pdf?sequence=1&isAllowed=y, except for population data which were retrieved from "Summary and Statistical Report of the 2007 Population and Housing Census. Population Size by Age and Sex", available at https://www.ethiopianreview.com/pdf/001/Cen2007_firstdraft.pdf.

Upon receiving the letter (which was personalized, i.e., addressed with the name of the respective pharmacy/drugstore), the recipient had to sign a copy as proof of receipt and as a form of "soft commitment device" (Bryan et al., 2010) that the pharmacy would adhere to the message in the letter.

The two letters had a similar introduction on the general emergence of antimicrobial resistance and the associated burden to the country and made it clear that the misuse of antibiotics is a key driver of antimicrobial resistance.[12] To reduce the cognitive load of the recipient, the letters were easy to read and to understand. Caution was also taken to ensure that they were of adequate length to capture the recipients' attention.

The coercive letter was a hard-tone message that reminded the pharmacists of the possibility of unannounced audits by the authority and of the ensuing applicable penalties in case of law infringement. The letter included the following information:

... according to the Ethiopian Food, Medicine and Health Care Administration and Control, Council of Ministers Regulation No. 299/2013, and Addis Ababa City Administration Food, Medicine, and Health Care Administration and Control, Council of Ministers Regulation No. 30/2012, it is illegal to dispense prescription medicines like antibiotics over the counter. The authority can undertake random audits of health facilities as needed. If misconduct is found, the authority will investigate and propose appropriate administrative measures as per the law, which can amount to suspension of license or certificate of competence.

This treatment, based on the deterrence model, assumes that "external forces" motivate good dispensing practices. It was intended to manipulate the pharmacists' expected financial incentives by making it clear that OTC antibiotics are illegal and that breaking the law has legal and pecuniary costs, which depend on the probability of being audited and the size of sanctions if found guilty.[13] Since AAFMHACA officials periodically undertake random audits of the

[12] The Appendix contains a translation of the letters into English.

[13] Field experiments using audit threats to discourage tax evasion include Fellner (2013), Castro & Scartascini (2015), and Pomeranz (2015). They are surveyed in Mascagni (2018).

pharmacies, the letter portrayed the true audit and accountability processes within Ethiopia and tried to influence the pharmacists' expectation of an audit.

The moral appeal letter appealed to the pharmacists' sense of altruism and duty of care. It praised the pharmacists as having a critical role in encouraging the rational use of antibiotics and further reminded them to advise customers requesting OTC antibiotics to go to the nearest health center for a proper diagnosis. An extract from the letter reads as follows:

……the authority reminds you to politely turn away patients looking to purchase an antibiotic without a prescription and further advise them to visit the nearest health center for proper diagnosis. In addition, you can contribute to safeguarding antibiotics by counseling patients on appropriate antibiotic use when prescribed and on antibiotic resistance, as appropriate.

This treatment was intended to influence the pharmacist's intrinsic motivations to limit antibiotic resistance and to induce pro-patient preferences. This soft-tone message could change the lens with which a pharmacist might view the requests of OTC antibiotics and could help tackle the cognitive bias of making decisions on short term benefits rather than considering the long-term impacts. Because the message in the letter stressed that the best course of action was for the patients to visit health centers, the moral appeal letter also stood to correct misperceptions about the role of the pharmacist in the healthcare system.[14]

Our third treatment required compulsory placement of a sticker on the pharmacy wall, in view of each customer entering the pharmacy. The sticker included a simple text message reminding the reader that antibiotics cannot be sold without prescription and encouraging him/her to help fighting antibiotic resistance, as shown in Figure 1.2.

Simple visual reminders, such as stickers, make information easy to communicate and it has been shown that they can alter people's behavior. In the context of long-distance minibus transportation in Kenya, for instance, Habyarimana & Jack (2011) find that stickers placed on the vehicles help to reduce road traffic accidents. In addition, as the sticker was in plain view of customers, this by itself may influence the pharmacist's behavior: since customer pressure

[14] Blumenthal et al. (2001) and Torgler (2004) used moral persuasion letters to enforce tax compliance in Minnesota and Switzerland, respectively.

is an important driver of antibiotic provision, and the presence of the sticker provides more leverage to the pharmacists to refuse the request of OTC antibiotics. The sticker is a reminder that can bridge the attentional gap between intention and action (Essl, Steffen & Staehle, 2021). On display inside pharmacy premises, the sticker makes it costly to propose an antibiotic to a customer that has not asked for it and at the same time it combats pushy clients as it is an official poster that backs up the decision of the pharmacist to deny antibiotics. It has essential implications for behavior and refocuses attention on the desired behavior (Karlan et al, 2016)

Figure 1. 2 Sticker placed on the pharmacy wall.

Most of the pharmacists receiving the coercive letter became defensive and claimed that they do not sell antibiotics without prescription. They were assured that the letter was not meant to accuse them, but simply to remind them of the penalties for doing so in the future. Recipients of the moral appeal letter diligently agreed with the message in the letter. The group of pharmacies receiving the sticker treatment welcomed the sticker and they even told the officials that it will save them wrangling with customers, particularly regulars.

1.4.3 Data collection and the Simulated Patient (SP) methodology

The sampling frame was constructed using the list of pharmacies/drugstores provided by the AAFMHCACA. At the time of the experiment, the total number of pharmacies (including both pharmacies and drugstores) was 891, stratified by sub-cities.

We made use of SPs to collect data on the pharmacists' willingness to sell OTC antibiotics. SPs are trained "fake patients" who go to health professionals and enact a predetermined scenario, while being undistinguishable from an authentic patient. In development research, simulated patients/mystery shoppers are becoming a significant and useful data collection

approach[15] Successfully and widely used in the medical literature, SPs have recently also been used in the health economics literature (e.g., Currie et al, 2014; Das et al., 2016).[16] Besides being employed to study health provider behaviour, mystery clients have been utilized in the contexts of testing for corruption (Bertrand et al., 2007), governance (Dizon-Ross, Dupas & Robinson, 2017) and police performance (Banerjee et al, 2021).

The biggest advantage of simulated patients is that it allows insight into actual transactions and the experiences of real customers or patients. But using simulated patients involves an element of deception and absence of consent (Fitzpatrick & Tumlinson, 2017). The deception and thus the potential harm to the subjects was relatively small as the experiment protocol was carefully designed to mimic real life interactions. In developing countries like Ethiopia, it is essential to address potential public health threats through accurate data collection that capture real behavior.

In addition, as part of a regular check and balance mechanism, routine random checks on pharmacies are common and healthcare providers are aware of these checks in their day-to-day operations. The research team members kept all observations and data therefrom strictly confidential. It was agreed from the start that no individual pharmacy/pharmacist related data, specific observations, behavior and findings would be communicated to the regulatory authorities and policy makers during and after the study. The main objective of the experiment was to estimate the nature and magnitude of non-prescription antibiotic requests and the interventions that are likely to reduce this phenomenon. Aggregated data from more than 800 interactions with pharmacies and drugstores were communicated to avoid any type of consequences for a particular pharmacy and/or professional. All identifying information will be destroyed on termination of the study.

We recruited a total of seven SPs (all middle-aged individuals) from Addis Ababa. Medical officers from health centers and AAFMHACA trained the SPs to present, in an accurate and

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[15] See https://blogs.worldbank.org/impactevaluations/mystery-clients-development-research

[16] Undercover experimenters (also called simulated agents) share the main characteristics of SPs and have been employed in economics to examine dishonest behavior in credence goods markets (e.g., Balafoutas et al., 2013; Kerschbamer et al., 2016).

consistent manner, one of two cases: a pediatric Upper Respiratory Tract Infection (URTI) and a female Urinary Tract Infection (UTI). The SPs trained for the URTI scenario presented themselves to the pharmacists as caregivers of a 2-year-old child with pneumonia and mentioned that they were hoping to purchase medicines from the pharmacy. The SPs trained for the female UTI scenario presented both symptom-based and product-based requests. A patient that describes the symptoms of her illness to obtain appropriate pain relief medicines may make her needs more salient or more serious than a patient asking for a specific product. This may change how the request is evaluated by a pharmacist with patient-regarding preferences.

We chose the URTI and UTI cases since they are frequent in Addis Ababa (Koji et al., 2019). Pediatric pneumonia is one of the most common childhood diseases in Ethiopia and represents a typical situation where antibiotics have been grossly abused, even for simple viral infections, in both clinical and pharmacy settings (Davey et al., 2002; Togoobaatar et al., 2010; Bhanwra, 2013). Likewise, female UTI is a common occurrence[17] in women and has fast become a challenge to treat due to resistant strains of the disease-causing pathogens (Paul, 2018).

The standardized scripts for the presentation of symptoms as well as predetermined answers to specific questions that the pharmacists could ask were pilot tested. The scripts for each scenario, presented in Table 1.2, were developed together with the AAFMHACA and health center officers. The SPs were told to purchase the antibiotic when offered, unless it was expensive (more than $3). If no antibiotic was offered, the SPs politely left the pharmacy.

Soon after exiting the pharmacy, the SPs filled in a questionnaire to record *i*) the type of visited community pharmacy (pharmacy or drugstore), *ii*) the time of the visit, *iii*) the pharmacist's gender and perceived age, *iv)* whether an antibiotic was sold, *v)* the requested price if sold, *vi*) any comments or advice given by the pharmacist.

[17] https://www.health.harvard.edu/blog/antibiotic-resistant-urinary-tract-infections-are-on-the-rise-2019101417982

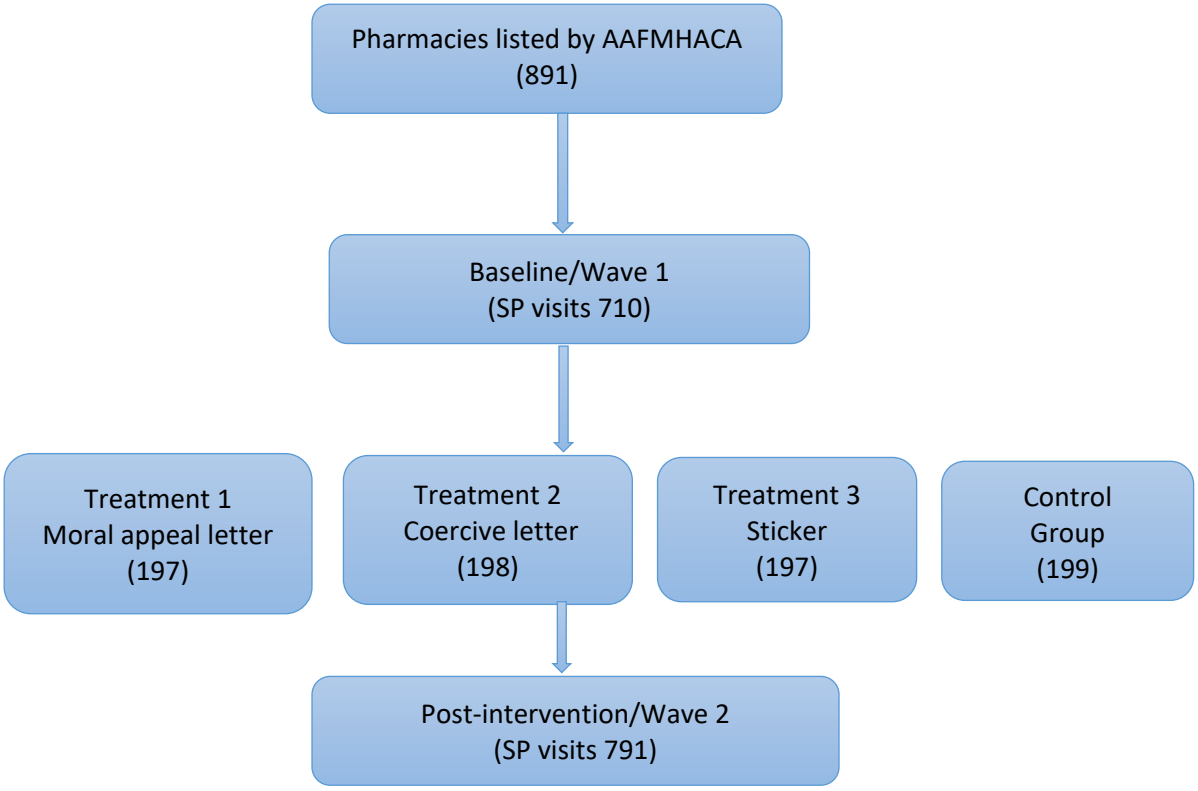
Table 1. 2 Details on scripts for SPs

Case	Script	Ideal management
Case 1-Pedieatric Pneumonia (Symptom-based)	The two-year-old son has been coughing for the past five days. He has slight fever and has been crying and whining. Request for anti-cough medicines. If asked about type of cough, the SP answers that the cough has sputum.	Advise visiting the nearest health center. Provide anti-fever medicine for immediate relief.
Case 2A - Female Urinary Tract infection (Symptom-based)	A lady client complains of burning sensation while urinating, chills, and slight fever. Requesting for pain relief medicines. The SP explains that this is a repeat condition and that she had similar experience before.	Advis visiting the nearest health center for diagnosis.
Case 2B - Female Urinary Tract infection (Product-based)	An informed lady client complaining of burning sensation while urinating, chills, and slight fever. Request for Cipro/Ciprofloxacin The SP explains that this is a repeat condition and that she had similar experiences and treatments before.	Advise visiting the nearest health center for diagnosis.

Since the cases presented were the same across treatments and extensive training was given to the SPs to ensure that they would behave in a similar manner, our study should have sound internal validity and hence be able to effectively assess the impact of the treatments on OTC sale of antibiotics. Additionally, since the SP method is covert, the pharmacists visited did not know that they were being observed, which should minimize the Hawthorne (or experimenter demand) effect, namely a change in behavior due to the awareness of being observed rather than to any of the three treatments (e.g., Dan et al., 2016; Björnsdottir et al., 2020; Collins et al., 2021). The ethics committee of the University of Amsterdam approved the study protocol.

Figure 1.3 shows the timeline of our experimental protocol. First, we randomly selected pharmacies from the list of 891 community pharmacies provided by AAFMHACA. For ease and convenience, the pharmacies were mapped on a city map according to their respective sub-cities. From May 5 to 20, 2019, we ran a first wave of data collection and gathered pre-treatment baseline data. In this wave, five SPs made 710 visits to pharmacies and drugstores. Afterwards (between June 24 and July 12), we administered our treatments, with pharmacies, randomized into three treatment arms and a fourth control (untreated) group. Two/three weeks after the intervention (from July 16 to August 16), we administered the second wave during which seven simulated patients visited 791 pharmacies.

Figure 1. 3 Experimental protocol



1.5 Results

1.5.1 Data set description and balance tests

Table 1.3 (columns 1−4) provides summary information on the sample of 710 visits made by the SPs in wave 1, before administering the treatments. Overall, 76.20% of the visits were to pharmacies and 23.80% to drugstores, 63.38% of all visits involved the UTI case, and, most importantly, averaging over all four groups, 54.23% of the visits resulted in an OTC sale of antibiotics.

Prior to running the primary analysis, we conducted balance tests to examine the extent to which the randomization procedures were successful in the sense that the observable characteristics of the pharmacies/drugstores visited in wave 1 were sufficiently similar across the four groups.

Table 1. 3 Summary information on baseline (wave 1) sample

		Coercive	Appeal	Sticker	Control	Coercive vs Control	Appeal vs Control	Sticker vs Control	Appeal vs sticker	Coercive vs Appeal	Coercive vs Sticker
		N=175	N=177	N=183	N=175	p-value	p-value	p-value	p-value	p-value	p-value
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
OTC antibiotic sales											
	Sold	93	105	93	94	0.915	0.289	0.584	0.105	0.243	0.66
	Did not sell	82	72	90	81						
Type of pharmacy											
	Pharmacy	139	137	143	122	0.037**	0.102	0.069*	0.866	0.644	0.766
	Drugstore	36	40	40	53						
Time of visit											
	Day	143	151	149	155	0.071*	0.364	0.059*	0.322	0.363	0.943
	Night	32	26	34	20						
Gender											
	Female	95	101	118	107	0.194	0.436	0.514	0.149	0.6	0.049*
	Male	80	76	65	68						
Case											
	UTI	112	109	116	113	0.911	0.561	0.816	0.723	0.639	0.904
	Pneumonia	63	68	67	62						
Product vs Symptom											
	Product	52	51	64	50	0.742	0.704	0.098*	0.209	0.957	0.187
	Symptom	60	58	52	63						

Notes: Unit of observation is "visit". The pharmacists' perceived age was not recorded in the baseline. Columns 5–10 report the p-values of pairwise comparisons using χ^2 test.
*Significant at 10%; **Significant at 5%; ***Significant at 1%.

Table 1. 4 Summary information on wave 2 sample

Variables	
Pharmacies visited	569
Drugstores visited	222
Total Pharmacies/drug stores visited	**791**
Pharmacies/drugstores visited before 5 pm	560
Female pharmacist/druggist	446
Average perceived age of pharmacist/druggist	37
Pharmacies/drugstores selling OTC antibiotics	287

The p-values of pairwise comparisons using chi-square tests are given in Table 1.3 (columns 5-10). The groups are well balanced for the main variable of interest: there is no significant difference in OTC antibiotic sales between any two groups (p-value > 0.10 for each of the six comparisons). For variables such as type of community pharmacy (pharmacy vs drugstore), time of visit (day vs night), and pharmacist's gender, we observe some heterogeneity across groups, although in most cases differences are significant at the 10% level. To control for this feature, we include these variables as covariates in the subsequent econometric analyses.

Table 1.4 gives details about the community pharmacies/pharmacists visited in wave 2, after administration of the treatments. Of the 791 community pharmacies visited, 71.9% were pharmacies and the remainder were drugstores. Many of these pharmacies/drugstores, 70.8%, were audited during daytime, i.e., before 5pm. The pharmacists' average perceived age was 37 years and 56.4% of the pharmacists were female. Notably, out of all 791 audited pharmacies, 36.3% sold antibiotics without a prescription.

1.5.2 Descriptive results

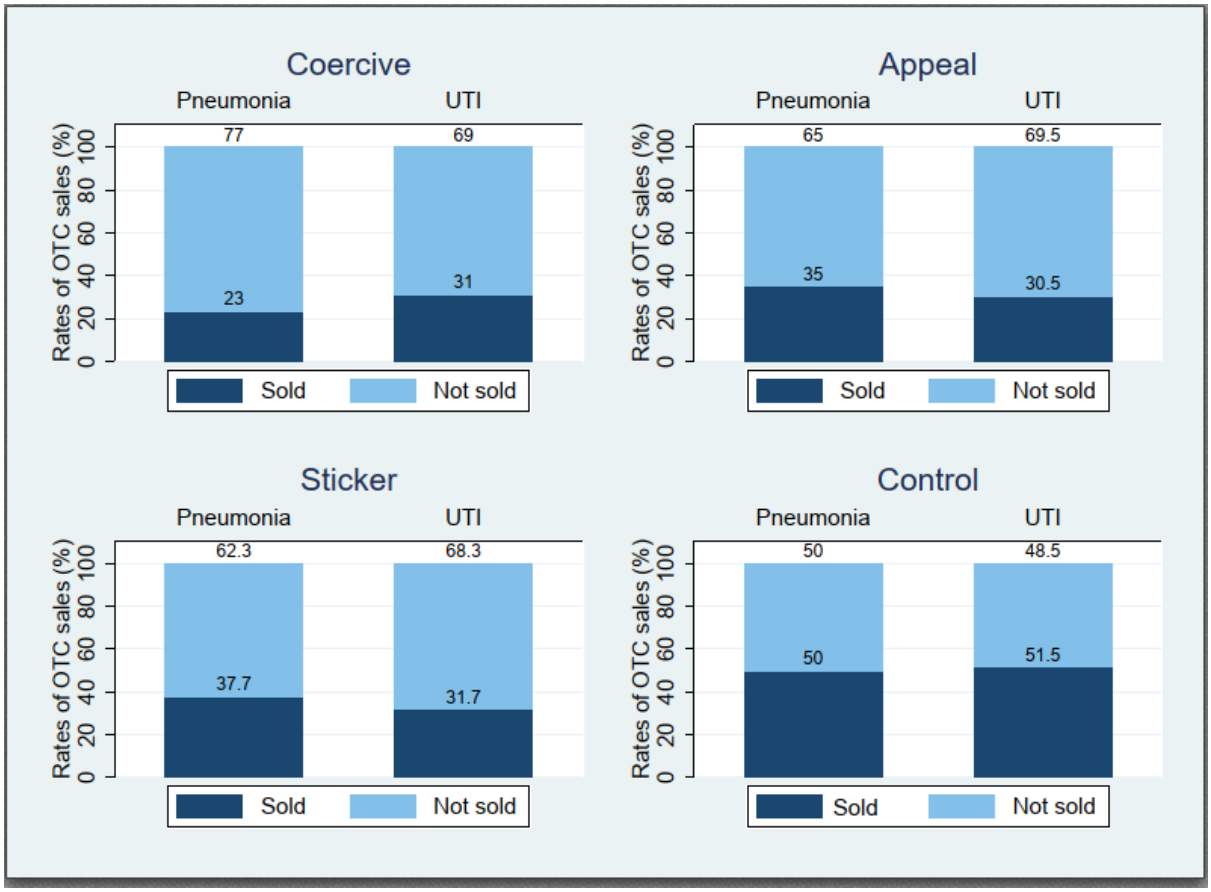
Figure 1.4 displays the frequency of sales of OTC antibiotics in wave 1 and wave 2, separately for each experimental treatment and the control. In the baseline wave 1, there appears to be no difference in the frequency of dispensing OTC antibiotics across the four groups: slightly more than 50 percent of the visited pharmacies sold OTC antibiotics in wave 1, whatever the group.

Figure 1.4 OTC antibiotic sales by wave and treatment

In contrast, following the intervention, dispensing decreases in all three experimental treatments, but not in the control: in wave 2, the percentages of pharmacies selling OTC antibiotics drop to 27.0, 32.8 and 34.5 percentage points for the groups treated with the coercive letter, the moral appeal letter, and the sticker, respectively; the percentage remains at about 50 for the control (untreated) group.

Wave 2 data are further separated by the case presented (URTI/pneumonia and UTI) and, for the UTI case, by whether the request was symptom-based or product-based in Figures 1.5 and 1.6, respectively. As to the different cases, we note that the group treated with the coercive letter sold OTC antibiotics for pediatric pneumonia only 23% of the time. For all other treated groups, percentages of OTC sales range from 30.5% (UTI case in the moral appeal treatment) to 37.7% (pneumonia case in the sticker treatment). The control group does not seem to display any substantial variation in the willingness to provide OTC antibiotics compared to the presented case.

Figure 1. 5 OTC antibiotic sales by case and treatment



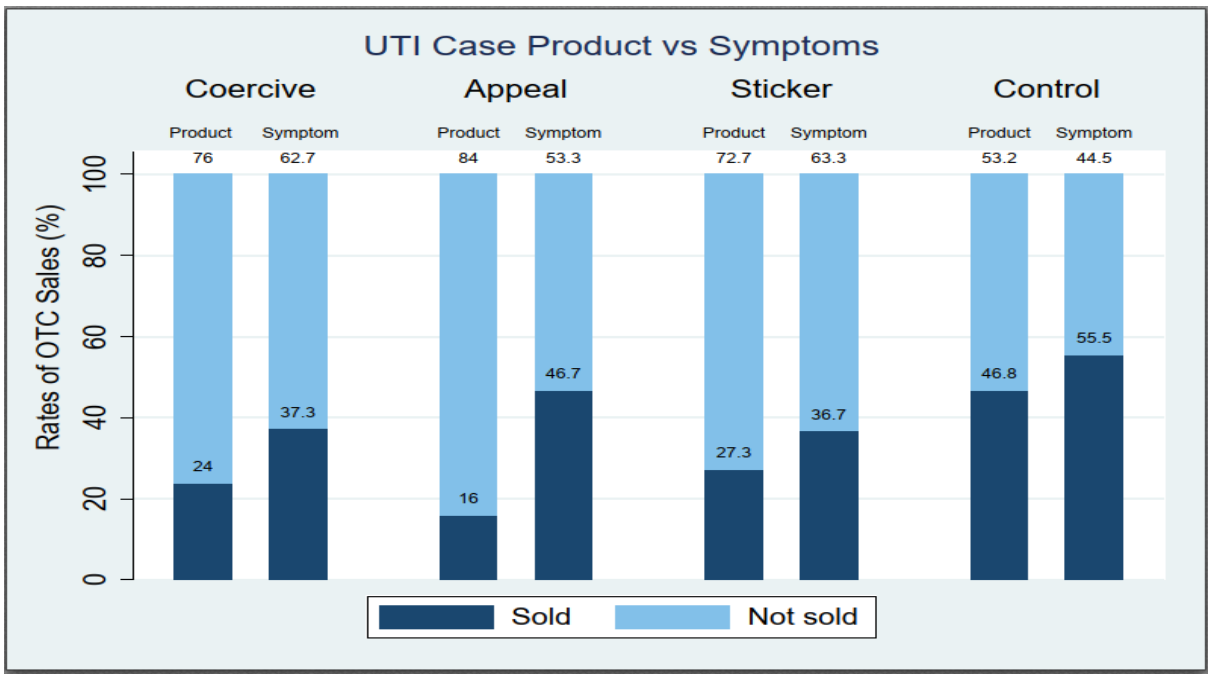
For the UTI case, whether the simulated patients requested a specific antibiotic or just presented the symptoms affects the rates of OTC antibiotics sales in all treatments: Figure 1.6 shows that more pharmacies sell antibiotics when the request is symptom-based. It seems therefore that pharmacists tend to be more willing to abide by the patient request if the needs are made salient, suggesting that they have patient-regarding preferences. When antibiotics were sold, pharmacists offered Amoxicillin[18] to the patients presenting with pneumonia. Pharmacists that refused to sell antibiotics often offered pain relief and allergy relieving medicines. For the UTI case, the commonly offered antibiotics belonged to the class of fluoroquinolone[19]

[18] This is an "access" drug according to the Aware Classification. Antibiotics in the access group are commonly used drugs with lower resistance potential compared to antibiotics in other groups.

[19] This is a "watch" drug according to the Aware Classification. Antibiotics in the watch group are at relatively high risk of selection of bacterial resistance and should be prioritized as key targets of stewardship programs and monitoring.

antibiotics and the SPs documented several interactions with the pharmacists who tended to diagnose sexually transmitted diseases and prescribed other antibiotics accordingly.

Figure 1. 6 OTC antibiotic sales for the UTI case by patient request (product-based vs symptom-based) and treatment



1.5.3 Estimation framework

The study implemented randomization at the pharmacy level. Random assignment ensures that there is no selection bias and comparing differences in the mean outcome variable can be used to draw inferences about the average treatment impact. In this situation, regression estimations provide a consistent estimate of the average treatment effect and using our experimental audit data we estimate the following specification:

$$Y_{ij} = \alpha + \beta_1 Coercive_{ij} + \beta_2 Appeal_{ij} + \beta_3 Sticker_{ij} + \beta_4 X_i + \varepsilon_{ij} \quad \ldots\ldots\ldots\ldots (1)$$

where Y_i is a binary variable equal to 1 if pharmacy i decided to sell OTC antibiotics to patient j; $Coercive_i$ is a dummy variable taking on the value of 1 if pharmacy i is in the coercive letter treatment and 0 otherwise; $Appeal_i$ is a dummy variable equal to 1 if pharmacy i is in the moral appeal letter treatment and 0 otherwise; $Sticker_i$ is a dummy variable indicating whether pharmacy i is in the sticker treatment. Finally, X_i represents a set of covariates that include

pharmacists' characteristics. One of the main issues with audit studies is that different patients may cause different behavior by the pharmacists. We thus control for patient fixed effects.

1.5.4 Estimation results

We report the impact of the coercive letter, the moral appeal letter, and the sticker on OTC sales of antibiotics for the full sample. The models were estimated with and without the full set of control variables, which are: the pharmacist's gender and perceived age, the time of the visit (day vs night), and the type of community pharmacy (pharmacy vs drugstore). Patient fixed effects, the kind of patient request (product-based vs symptom-based), and ten sub-city dummies (with sub-city 1 as the reference category) were also included. The results of the Probit regressions are presented in Table 1.5 (first two columns). We note that all three interventions had a significant impact on reducing the non-prescription sales of antibiotics.

Controlling for observable characteristics and patient fixed effects has remarkably little effect on our estimates. The coercive letter has the highest impact: it reduces OTC antibiotics by 23.4 percentage points compared to the control group and the coefficient is significant at the 1% level. The moral appeal letter reduces the dependent variable by 16.5 percentage points and the corresponding coefficient is highly significant. Pharmacies assigned to the sticker treatment sell 13.5 percent less OTC antibiotics compared to the control group and the effect is significant at 5% level. The results further suggest that the three treatments are similarly effective in reducing non prescribed antibiotics. We cannot reject the null hypothesis that the coercive letter, moral appeal and sticker treatments have the same impact on sales of antibiotics (p = 0.2301 Wald test). As to the control variables, drugstores are more likely to sell OTC antibiotics compared to pharmacies and patients requesting a specific antibiotic are more often turned away without being offered the product compared to patients describing symptoms. We also estimated marginal effects using logistic regressions and our results remain robust (see models 3 and 4 in Table 1.5).

When refusing to sell, treated pharmacists were more likely to explain the reason for denial than untreated pharmacists. The top reason for refusal was that a prescription for antibiotics was necessary. This was followed by the importance of visiting a medical doctor or getting a clinical laboratory test (particularly for the UTI) to confirm the infection and thus the need for antibiotics.

Table 1. 5 Decision to sell OTC antibiotics

Independent Variables	Probit (marginal effects)	
	3	4
Coercive	-0.23***	-0.234***
	(-0.0451)	(0.044)
Appeal	-0.167***	-0.165***
	(0.045)	(0.044)
Sticker	-0.15**	-0.135**
	(0.045)	(0.044)
Female Pharmacist		-0.040
		(0.035)
Age		0.004*
		(0.002)
Day		-0.070
		(0.036)
Store		0.071*
		(0.035)
UTI-Product		-0.109*
		(0.048)
UTI-Symptom		0.042
		(0.046)
Constant	0.03	-0.488
	(0.141)	(0.431)
R-squared	0.026	0.038
Simulated Patient Dummy	NO	YES
Sub-city dummy	NO	YES
Controls	NO	YES
Number of Observations	791	790

The above analysis of the frequency of dispensing OTC antibiotics gives a good indication of the extensive margin, i.e., of how many pharmacists willingly provided OTC antibiotics. However, the treatments may work on both the extensive and intensive margins. In developing countries like Ethiopia, prices for pharmaceutical products are often not posted and receipts are uncommon (Fitzpatrick & Tumlinson, 2017). In addition, the price range observed among different pharmacies is wide. Drug prices are not regulated in Ethiopia and there is no agreed upon method or legally enforceable mechanism to determine the final price paid by the patient for the drugs. Therefore, products that are mostly imported from various countries can have broad price variations especially in private pharmacies. The median price for common antibiotics were $4.1 and $2.7 dollars respectively, in private and public pharmacies. The pharmaceutical pricing situation is characterized by the absence of a clear medicines pricing policy, high retail markups, and steep variations in the price of medicines. This is particularly

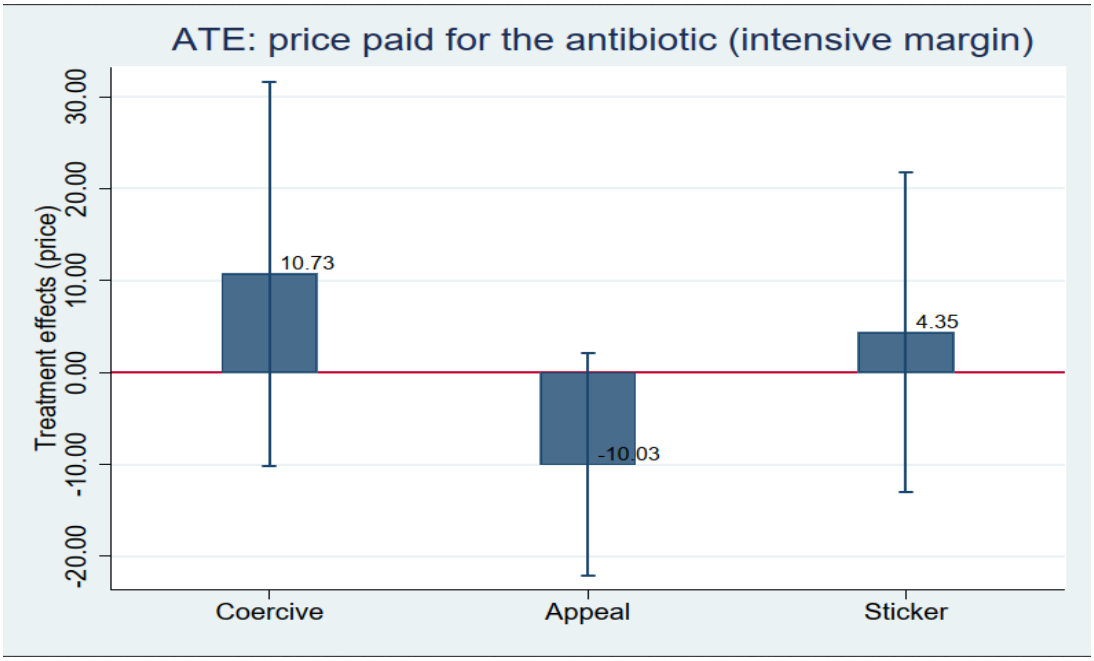
the case for the private pharmacies where price variations for antibiotic products are largely due to the nonexistence of enforced price markups (Gutema & Engidawork,2018)

It is plausible that treated pharmacies may perceive their offer of antibiotics as a risky activity that warrants some premium and thus may sell the antibiotics at a much higher margin. We therefore assess whether the interventions had any impact on the prices of the antibiotics that were offered because unethical pharmacists may decide to offset the loss in revenue due to a decrease in the quantity sold by a price hike. We used OLS regressions to estimate the average treatment effect (ATE) of the interventions on the price paid for the antibiotic, controlling for all relevant background characteristics. The estimation results are shown in Table 1.6 and Figure 1.7, which reveal that no treatment has any significant effect on price. We thus conclude that our interventions mainly worked on the extensive margin, which is crucial for the welfare implications of our treatments.

Table 1. 6 Average treatment effect (ATE): price paid for antibiotics (intensive margin)

Independent Variables	OLS	
	1	2
Coercive	10.725	7.699
	(10.641)	(10.444)
Appeal	-10.029	-12.48
	(6.145)	(6.677)
Sticker	4.352	2.460
	(8.833)	(8.796)
Female Pharmacist		-3.389
		(6.945)
Age		-0.183
		(0.382)
Day		5.431
		(6.783)
Store		-11.651*
		(5.608)
UTI-Product		1.523
		(11.137)
UTI-Symptom		10.424
		(8.202)
Constant	65.029***	69.141**
	(4.590)	(21.539)
R-squared	0.017	0.0721
Simulated Patient Dummy	NO	YES
Sub-city dummy	NO	YES
Controls	NO	YES
Number of Observations	287	287

Figure 1. 7 Price effects of the interventions



Notes: The height of each bar represents the coefficients of model (1) in Table 1.6 and its 95% confidence interval. The graph is indicative of the absence of significant treatment effects on price.

1.6 Conclusions and future directions

Antibiotic resistance is shrinking the range of antibiotic drugs for effective treatment and is a worldwide public health problem. Acknowledging that it is not only a medical problem, but also a behavioral and social one, concerted efforts are required to reduce the unjustified consumption of antibiotics at all levels. Unlikely to be bailed out by advances in new antibiotics, to ensure the justified access to antibiotics and their future sustainability is a task that entails tackling the myriad drivers of non-optimal use.

With the aim of sensitizing drug retailers and pharmacy personnel about the dangers of OTC antibiotics, this study provides unique evidence on rule compliance by way of the random allocation of different messages. Our study presents evidence that very cheap interventions can alter the behavior of pharmacists and curtail antibiotic abuse. Our results suggest that close to 50 percent of pharmacies in Addis Ababa provide OTC antibiotics to clients. This rate declines significantly for pharmacies receiving any of the treatments, indicating that cheap interventions can help change pharmacists' behavior at least in the short run. Regulatory health authorities

may thus think of employing these types of nudges as part of their control toolbox to sensitize and optimize antibiotic dispensing.

Although our simulated patient experiment could only capture a limited number of Ethiopian pharmacies, it is well known that many people in Ethiopia visit pharmacies and ask for OTC antibiotics daily. A modest estimate of 1 per 100 people purchasing and consuming OTC antibiotics annually suggests that 10,000 persons in a population of one million are self-medicating annually. For Ethiopia, this modest estimate implies that 1,120,000 people self-medicate yearly. Given the extent of the OTC antibiotic provision found in Addis Ababa in this study, the situation in smaller towns and rural areas is not hard to visualize. The welfare effects of our interventions may be larger if this feature is accounted for.

We observed the effect of the interventions on the pharmacists' likelihood to dispense OTC antibiotics, but we did not provide any evidence of a decrease in total antibiotics sales. Patients who did not get OTC antibiotics by pharmacists may have visited a medical doctor to obtain a proper prescription. In low-income countries like Ethiopia, there is a need to balance access and the excess of antibiotics.

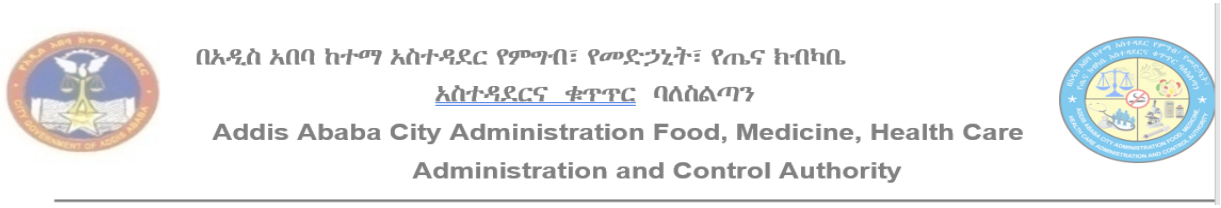
Even though the norm of compliance is non-controversial and has many benefits, our design may have resulted in an error if truly needy patients – who cannot afford to visit health centers – were refused antibiotics. In such a scenario, the real impact on the patient's health outcomes and society's welfare may be ambiguous and sometimes backfire. Hence, it may be useful to combine our nudge-like interventions with a policy that gives patients easy access to doctors and healthcare in general. For example, community pharmacies could provide patients with free vouchers to visit the nearest health center.

Regulating sales of antibiotics is undoubtedly relevant to promoting appropriate use. Yet, this is only one component of a more comprehensive strategy required to tackle antibiotic resistance. The effectiveness of antibiotics is also influenced by how antibiotics are prescribed by medical doctors and by patient compliance with antibiotics dosages. In a broader sense, Willis & Chandler (2019) argue that attention needs to move away from the more commonplace binary of 'appropriate/inappropriate' antibiotic use and focus on fixing the reasons for ingrained antibiotic use in developing countries. The argument is that obscuring antibiotic abuse as a problem of individual behavior shifts attention from underlying structural

problems in developing countries. However, since self-medication with antibiotics is a ubiquitous reality, our findings confirm that simple low-cost interventions sparked desirable actions and impacted on pharmacists' behavior. It then becomes important to examine the persistence of the observed effect and check if it continues to hold for a longer period. We examine this issue in the next chapter.

Appendix 1:

A.1.1: Text of the "coercive letter" (originally in Amharic)



Date:----------

Ref. No._____

To: XYZ Pharmacy/Drugstore

Addis Ababa

Subject: Over the Counter Sales of Antibiotics

As you are aware, bacterial infections induced diseases like pneumonia, tuberculosis and diarrhoea etc are the major causes of death in Ethiopia. The emergence of antimicrobial resistance threatens the management of bacterial infections. Antimicrobial resistance is a result of the use, overuse and misuse of antibiotics. In Ethiopia, there are indications on the misuse of antibiotics by healthcare providers, unskilled practitioners, and drug consumers. One common channel of abuse is the sales of non-prescribed antibiotics for diseases like sore throat, common cold and diarrhoeal diseases. In a recent audit of pharmacies by experts, the Addis Ababa Food, Medicine and Health Care Administration and Control Authority AAFMHACA found numerous counts of noncompliance with the regulations of the pharmaceutical sector.

The authority reminds you that according to the Ethiopian Food, Medicine and Healthcare Administration and Control, Council of Ministers Regulation No. 299/2013, and Addis Ababa City Administration Food, Medicine and Healthcare Administration and Control, Council of Ministers Regulation No. 30/2012, it is illegal to dispense prescription medicines like antibiotics over the counter. The authority can undertake random audits of health facilities as needed. If misconduct is found, the authority will investigate and propose appropriate administrative measure as per the law, which can amount to suspension of license or certificate of competence.

Given these consequences, the authority advises you against non-prescription sales of antibiotics.

Regards,

A.1.2: Text of the “morally appeal letter” (originally in Amharic)

በአዲስ አበባ ከተማ አስተዳደር የምግብ፣ የመድኃኒት፣ የጤና ክብካቤ
አስተዳደርና ቁጥጥር ባለስልጣን
Addis Ababa City Administration Food, Medicine, Health Care
Administration and Control Authority

Date: ----------

Ref. No._____

To: XYZ Pharmacy/Drugstore

Addis Ababa

Subject: Over the Counter Sales of Antibiotics

As you are aware, bacterial infections induced diseases like pneumonia, tuberculosis and diarrhoea etc are the major causes of death in Ethiopia. The emergence of antimicrobial resistance threatens the management of bacterial infections. Antimicrobial resistance is a result of the use, overuse and misuse of antibiotics. In Ethiopia, there are indications of the misuse of antibiotics by healthcare providers, unskilled practitioners, and drug consumers. One common channel of abuse is the sales of non-prescribed antibiotics for diseases like sore throat, common cold and diarrhoeal diseases. In a recent audit of pharmacies by experts, the Addis Ababa City Administration Food, Medicine and Health Care Administration and Control Authority AAFMHACA found numerous counts of noncompliance with the regulations of the pharmaceutical sector. The Authority believes that you as a pharmacist have a critical role to play in encouraging rational use of medicines and curtailing Antibiotic resistance.

In the pursuit of the same, the authority reminds you to politely turn away patients looking to purchase an antibiotic without prescription and further advise them to visit the nearest health centre for proper diagnosis. In addition, you can contribute to safeguarding antibiotics by counselling patients on appropriate antibiotic use when prescribed and on antibiotic resistance, as appropriate.

Given the pharmacist’s unique position in the health system, the authority advises you to take a lead role in combating antibiotic resistance.

Regards,

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Chapter Two

The Persistent and Heterogeneous Effects of Nudging the Pharmacist to Combat the Non-Prescription Sales of Antibiotics

2.1 Introduction

Nudges – defined as interventions, suggestions, or gentle hints that seek to "maintain freedom of choice while also steering people's decisions in the right direction (as judged by people themselves)" (Sunstein, 2014, p. 17) – have been receiving a considerable amount of attention from both researchers and policymakers. They enable the handling of policy and societal problems in a way that increases wellbeing without jeopardizing individual liberty.[20] The identification of heuristics in individuals' decision-making processes has opened up a world of possibilities for public administrators and regulators to develop behaviorally informed policies. As a result, a number of governments – including the UK, Australia, Germany, the Netherlands, and the US – have established "nudge units" with the aim of applying insights from the social and behavioral sciences to policy initiatives and encouraging individuals to make decisions that improve private and social welfare (Bernedo et al., 2014; Cai, 2019).

One concern with nudges is that they are often provided either once or on a short-term basis and may fail to produce long-term and consistent changes in behavior (Raihani, 2013; Brandon et al., 2017). This concern is particularly acute when nudges aim to produce outcomes that involve a series of decisions. The behavioral policy literature, particularly the nudge literature, is infamous for studies in which individuals' behavior returns to pre-intervention levels after the nudge is removed. Meier (2007), Acland & Levy (2015), Levitt et al. (2016) have shown that treatment effects rarely endure after withdrawal of the nudge and when they do, they dissipate quickly. The sustained impact of nudges has, for instance, significant implications for their cost effectiveness. While many researchers acknowledge the importance of assessing the extent to which the behavioral change induced by the nudge persists (Beshears & Kosowsky,

[20] Many nudges are "paternalistic", i.e., designed to increase the benefits to both the society and the nudged individuals (Thaler & Sunstein, 2003). However, there are cases in which nudges, while maximizing social wellbeing, require the nudged individuals to pay some costs (see Raihani, 2013, for examples of non-paternalistic nudges).

2020), the existing evidence on the long-run effects of nudges is relatively scant. In their review on nudge treatment effects, Beshears & Kosowsky (2020) find that only 17 out of the 174 surveyed articles collect follow-up data to estimate the effect of at least one treatment in the long run.[21]

Another potential problem with nudges is that their efficacy may vary across contexts and groups of people (Raihani, 2013; Athey and Imbens, 2016). Average effects of a particular nudge intervention can mask substantial variations in how particular individuals and subgroups respond to the nudge. One would like to know, if possible, the heterogeneity of responses among different subgroups as well as the mechanisms via which the nudges influence behavior (Ferraro and Miranda, 2013). This opens the door for targeted nudges rather than universal nudges: since any nudge-type intervention may have different effects on different people, the intervention can be targeted more cost-effectively to a specific audience by discerning the most responsive subgroups.[22] Additionally, from a more general point of view, the identification of heterogeneous responses can improve the generalizability and external validity of findings of randomized controlled trials (Hotz et al., 2005; Allcott & Mullainathan, 2010a; 2010b; Imai & Ratkovic, 2013). The average effects of an experiment may indeed be different if applied to other samples with different distributions of observable characteristics Finally, using the information on the heterogeneous responses in combination with theory may help assess likely mechanisms through which the causal effects are created.

More research is thus called for to understand the context in which certain nudges work, for how long, on whom, and how they work. Herein, we provide evidence of the persistent and heterogeneous effects of the three one-time nudge interventions designed to restrict over-the-counter (OTC) antibiotics in Ethiopia described in Chapter 1. Let us just briefly recall the main features of the design. Community pharmacies in Addis Ababa were assigned, at random, into one of four groups: *i*) a control (untreated) group, *ii*) a group that received a coercive letter

[21] Some of the studies investigating the longevity of the effects from nudges are reviewed in the next section.

[22] As pointed out by Djebbari & Smith (2008), politicians prefer interventions that give small benefits to many people while harming none (information that cannot be obtained by focusing on average effects) and policy analysists would like to prioritize interventions based on social welfare functions that allow for heterogeneity in individual characteristics and attitudes.

targeted to make salient the legal consequences of engaging in sales of non-prescribed antibiotics, *iii*) a group that received a moral appeal letter that invoked the pharmacists' sense of duty of care, and *iv*) a group that received a sticker to be placed on the pharmacy's wall with messages reminding the reader that antibiotics cannot be sold without prescription. To measure the outcome – i.e., pharmacists' willingness to sell antibiotics without prescription – simulated patients visited the pharmacies and, using a predefined script, presented one of two cases: a pediatric Upper Respiratory Tract Infection (URTI) and a female Urinary Tract Infection (UTI).

To study the longevity of the effects of our treatments, we collected outcome data on OTC sales of antibiotics five months after the interventions. Hence, the pre-intervention (baseline) wave 1 and the post-intervention wave 2 (examined in the previous chapter and carried out two to three weeks after the administration of the treatments) were followed by a third wave (at five months from the interventions). To estimate heterogeneous treatment effects, we selected covariates (subgroups) that could be important modifiers of the effects and that are commonly observable – namely, pharmacists' gender and perceived age, type of community pharmacy, and time of the visit.

The results of a difference-in-difference analysis between treated and non-treated groups across the three waves indicate that our nudge interventions have a persistent effect: they are effective well into the fifth month, despite some waning for the groups of pharmacies treated with the two letters. The heterogeneity analysis proves that these findings are robust across the different subgroups considered. Hence, the low-cost nudge interventions proposed here have the potential to be important tools in the health regulators' toolbox encouraging pharmacists to abide by appropriate dispensing practices and combat antibiotic abuse.

We structure the chapter as follows. The following section reviews the most relevant literature. Section 3 sketches the experimental design, which was explained in detail in Chapter 1. Section 4 presents the initial descriptive statistics and then estimation results from econometric models. Section 5 concludes.

2.2 Literature review

In the past decades, nudges have been applied in different domains including health (e.g., Johnson & Goldstein, 2003; Thornton, 2008; Volpp et al., 2008; Giné et al., 2010; Hunter et al., 2012), tax compliance (e.g., Chetty et al., 2008; Fellner et al., 2013; Hallsworth, 2014; Shimeles et al., 2017; Bott et al., 2020), savings (e.g., Madrian & Shea, 2001; Thaler & Benartzi, 2004), environmental protection (e.g., Kallbekken & Sælen, 2013), energy conservation (e.g., Allcott & Rogers, 2014), agriculture (e.g., Duflo et al., 2011; Peth et al., 2018; Chabé-Ferret et al., 2019), and education (e.g., Blimpo, 2014; Castleman & Page, 2015; Himmler et al., 2019).

Despite their abundant application in empirical research, studies assessing which nudges persist and under what conditions are relatively scarce. Brandon et al. (2017) observe that in recent years there have been some field experiments designed to test the theoretical predictions of Becker & Murphy's (1988) model of "habit-formation".[23] They take into account ten studies that have in common *i*) the introduction of a financial incentive to induce a behavioral change, and *ii*) the analysis of behavior during and after the incentive is introduced. By looking at the proportion of the incentive effect that persists after the removal of the incentive, Brandon et al. (2017) note that treatment effects rarely persist (in only four of the ten studies, behavior is consistent with the formation of a habit) and when they do persist, they appear to diminish over time. Charness & Gneezy (2009), for instance, show that financial incentives to exercise at the gym help in the short run, but their positive effect steadily decays over time and eventually vanishes after about two years.

Unlike the studies analyzed by Brandon et al (2017), Schaner (2018) document relatively persistent impacts of temporary, but high-powered, financial incentives to save on economic outcomes. In his study, participants (people living in rural Kenya) who receive large temporary interest rates on an individual bank account have significantly more income and assets in the long run, namely 2.5–3.5 years after the interest rates expired. Royer et al. (2015) find that, while the effect of a one-month financial incentive for gym attendance fades quickly, the

[23] In a traditional habit formation model, the change in behavior prompted by the nudge leads to an increase in habitual capital. Becker & Murphy (1988) identify the conditions under which one's past consumption of a good raises one's marginal utility of present consumption.

availability of a commitment option at the end of the incentive program significantly improves the long-run effect of the intervention, with changes detectable even two to three years after the incentive ended.

The persistence of treatment effects when nudges involve targeted messages has been examined by Ferraro et al. (2011), Allcott & Rogers (2014), and Bernedo et al. (2014), among others. Using data from a randomized controlled trial run by a water utility in Atlanta (Georgia) to reduce water use during a drought, Ferraro et al. (2011) show that messages including social comparisons (which contrast the household's water use to that of the average consumer) have an impact on water use that lasts two years after the message was sent. Bernedo et al. (2014) extend the analysis of Ferraro et al. (2011) by considering four additional years of data and find that the effect of the social comparison nudge decreases over time but remains detectable in the fourth year.[24]

Allcott & Rogers (2014) study the Home Energy Reports produced by the company Opower in the US. The reports, featuring a social comparison nudge that compares the household's energy consumption to that of similar neighbors, are mailed to households periodically for either a limited period (about two years) or without limit. Allcott & Rogers find that consumers reduce their energy use significantly after receiving their reports, but at a rate that may cause the effect to disappear after a few months if mailings are not repeated. Treatment effects in the third through the fifth years from the initial mailing are significantly stronger if the intervention is continued rather than discontinued, which leads the authors to conclude that consumers gradually change their capital stock of habits or physical technologies.

In the context of tax compliance, Fellner et al. (2013) examine the persistent effect of using mailings with different texts to encourage potential evaders to pay TV license fees in Austria. They find that neither a moral appeal letter emphasizing that compliance is a matter of fairness, nor a social information letter highlighting the high level of compliance in Austria have an effect beyond the baseline letter. In contrast, a threat letter that makes detection risk salient has

[24] The treatment effect survives for seven years by restricting the sample to the subset of households that did not move during the time span considered.

a significant impact on compliance, but the effect is short-lived as study participants are likely to cancel their registration for license fees half a year after the experiment.

In 2018, the Superintendence of the Tax Administration of Guatemala gauged the ongoing impact of a nudge nationwide intervention that started in 2015 and was designed to encourage people to pay their taxes.[25] The intervention involved the delivery of letters to taxpayers who were late in the payment of their income tax. Some letters referred to social norms and highlighted that those who had not yet filed their taxes were part of a minority; others referred to the non-filing as an intentional choice and emphasized the risk of being audited. The intervention was found to prompt a significant increase in tax collection, which endures over time (one year after sending the messages) with no need of a reminder.

Several aspects of a nudge design can explain persistency. Features of the "choice architecture" – which organizes how participants interact with the system and how choices are framed or presented (Thaler & Sunstein, 2008) – play an important role in the longevity of the nudge. Cronqvist et al. (2018) make this clear when they study the choice architecture of the Swedish Premium Pension Plan, launched in 2000, and find that the effect of nudging in this case endures for nearly 20 years. The route from nudges to persistent changes in behavior is influenced by the salience of the nudge as well as by the nudged individuals' biases and preferences. Despite the mixed evidence on the long-run effects of nudge interventions, it is unquestionable that the relative lack of studies on this subject goes hand in hand with the increasing interest from researchers and policy makers in assessing whether or not one-time nudge interventions have long-lasting effects.

Our study is also related to the literature examining heterogeneity in the effects of nudges. The relevance of uncovering heterogeneous treatment impacts of nudge interventions has been acknowledged by, e.g., Djebbari & Smith (2008) who investigate heterogeneity in the effects of a Mexican conditional cash transfer program on per-capita consumption and provide evidence of subgroup variation in impacts of the program. Allcott & Mullainathan (2010b) analyze 14 energy conservation field experiments run by the company Opower in a number of different sites across the U.S and document statistically and economically significant

[25] See https://blogs.worldbank.org/voices/ongoing-impact-nudging-people-pay-their-taxes

heterogeneity in treatment effects across sites. The effect of the social comparison nudge featured by Opower is also found to depend on political ideology: US households with politically liberal ideology are more likely to reduce energy use in response to the nudge compared to conservative households (Costa & Kahn, 2013).

Ferraro & Miranda (2013) estimate heterogeneous household responses using data from the randomized controlled trial intended to reduce water use in Atlanta (Georgia). They find that messages including social comparisons exhibit strong heterogeneity: wealthier households, owner-occupants, and households that consume more water are more responsive to the messages.

The results of these studies are suggestive of the importance of assessing heterogeneity in various subgroups to come up with targeted nudges, which may be more effective in producing the intended behavioral changes.

2.3 Study design

Here, we only sketch the main features of the experimental design.[26] In collaboration with the Addis Ababa Food Medicine Health Care Administration and Control Authority (AAFMHACA), two types of letters and a sticker reminder aimed at curbing OTC antibiotics were sent to randomly selected groups of pharmacies and drugstores in Addis Ababa. Our sample is quite heterogeneous with regard to location as these community pharmacies span the different sub-cities in the capital (see Figure 1.1 in Chapter 1). The introductory paragraph in both letters provided information on the twin problems of drug resistance and the trends of OTC antibiotics in Addis Ababa. The second paragraph in the coercive letter made the argument for random audits of pharmacies by the authorities and reminded pharmacists of the punishments in case of dispensing malpractices. The second paragraph in the moral appeal letter advised the pharmacist to refer patients requesting antibiotics to the nearest health center. The informational sticker advocated against the sales of non-prescription antibiotics and was placed on the walls of the pharmacies in a location likely to be visible to the customers.

[26] For further details, see Section 4 in Chapter 1.

The data were collected by eleven simulated patients (SPs) who visited the pharmacies requesting OTC antibiotics for either a pediatric Upper Respiratory Tract Infection (URTI) or a female Urinary Tract Infection (UTI). The SPs used standardized scripts, which were pilot-tested and developed together with the AAFMHACA and health center officers.

We collected three waves of data on the outcome variable: wave 1 gathered pre-treatment baseline data, while waves 2 and 3 were carried out, respectively, two/three weeks and five months after administering the treatments. Wave 3 was implemented in November/December 2019. Table 2.1 displays the number of pharmacies visited by the SPs in each treatment, separately for each wave.

Table 2. 1 Number of visited pharmacies by treatment and wave

	Control	Coercive	Appeal	Sticker	Total
Wave 1 (Pre-intervention)	175	175	177	183	710
Wave 2 (3 weeks after)	199	197	198	197	791
Wave 3 (5 months after)	206	191	196	192	785

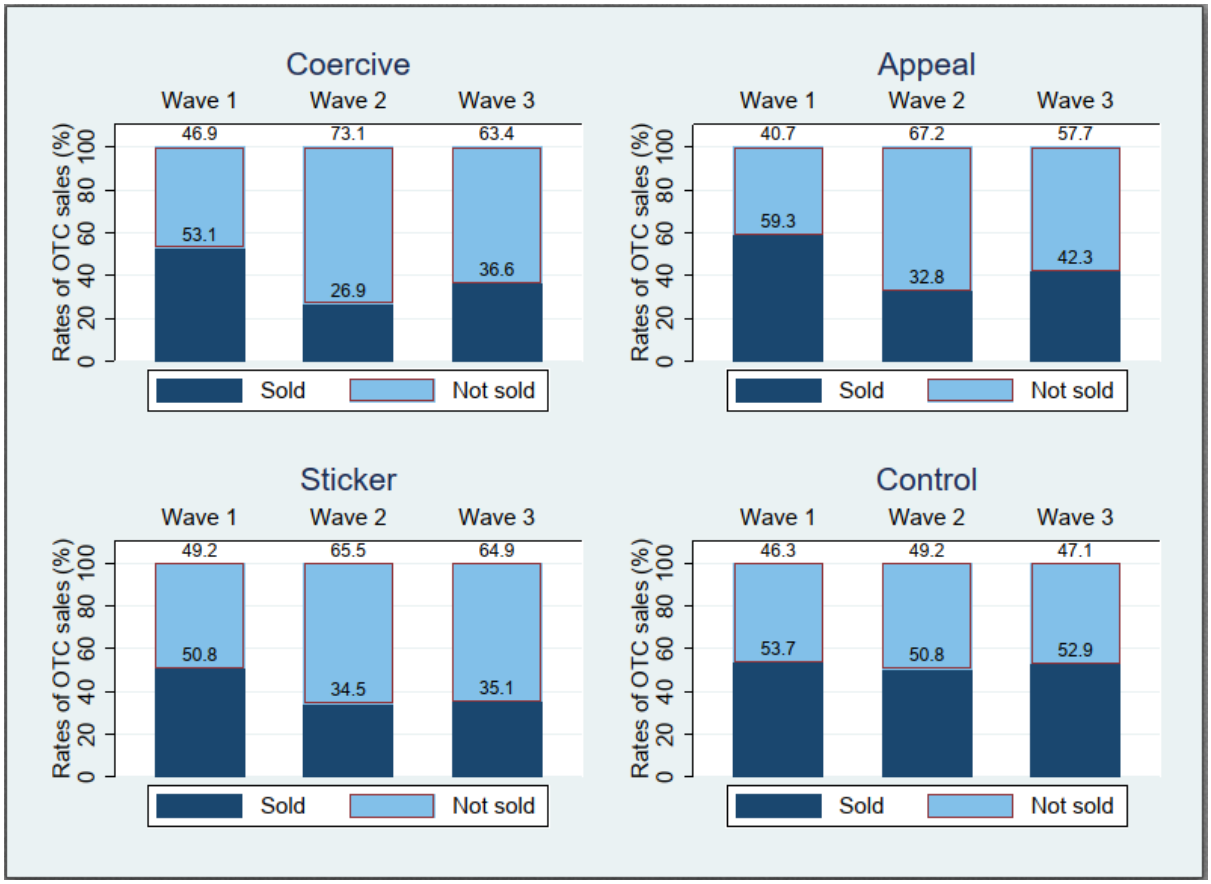
2.4 Results

2.4.1 Descriptive results

We first present a piece of model-free evidence by plotting the frequencies of OTC antibiotic sales in the treatment and control groups for each of the three waves. Figure 2.1 shows such frequencies. All four groups are remarkably close to each other in terms of their pre-treatment average sales of OTC antibiotics. After the launch of the intervention, the three treated groups immediately reduce their OTC sales, as wave 2 data indicate. In wave 3, sales of OTC antibiotics increase compared to wave 2, but continue to be lower than the pre-treatment sales levels.

When refusing to sell, many pharmacists explained to the SPs that a prescription paper was needed to sell antibiotics and/or that it was necessary to see a medical doctor. For the UTI patients, some pharmacists stepped forward to provide additional advice that included drinking adequate water and hygiene-related recommendations.

Figure 2. 1 Frequency of OTC antibiotic sales by treatment – All waves



2.4.2 Estimation framework

To investigate the persistence of the interventions, our empirical strategy exploits the panel nature of our data and employs Difference-in-Difference (DiD) models based on Card and Krueger (1994). The two models, presented in Equations (1) and (2), make use of pharmacy and patient interaction data over the three waves. The model reported in Eq. (1) is used to estimate the DiD treatment effects compared to the control group. The model reported in Eq. (2) is used to estimate the DiD effects compared to the previous wave.

$$Y_{it} = \alpha + \alpha_c dC_i + \alpha_A dA_i + \alpha_s dS_i + \alpha_2 w2_t + \alpha_3 w3_t + \boldsymbol{\beta_{c2}}(dC_i * w2_t) + \boldsymbol{\beta_{A2}}(dA_i * w2_t) + \boldsymbol{\beta_{S2}}(dS_i * w2_t) + \boldsymbol{\beta_{c3}}(dC_i * w3_t) + \boldsymbol{\beta_{A3}}(dA_i * w3_t) + \boldsymbol{\beta_{S3}}(dS_i * w3_t) + \gamma X_{it} + \delta Z_i + \epsilon_{it} \quad (1)$$

$$Y_{it} = \alpha + \alpha_c dC_i + \alpha_A dA_i + \alpha_s dS_i + \alpha_2(w2_t + w3_t) + \alpha_3 w3_t + \boldsymbol{\beta_{c2}}\big(dC_i * (w2_t + w3_t)\big) + \boldsymbol{\beta_{A2}}\big(dA_i * (w2_t + w3_t)\big) + \boldsymbol{\beta_{S2}}\big(dS_i * (w2_t + w3_t)\big) + \boldsymbol{\beta_{c3}}(dC_i * w3_t) + \boldsymbol{\beta_{A3}}(dA_i * w3_t) + \boldsymbol{\beta_{S3}}(dS_i * w3_t) + \gamma X_{it} + \delta Z_i + \epsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

In both models, Y_{it} is a binary variable equal to 1 if pharmacy i decided to sell OTC antibiotics at wave t. dC_i, dA_i, and dS_i are treatment dummies indicating whether pharmacy i received the Coercive letter, the moral Appeal letter, or the Sticker, respectively. $w2_t$ is a dummy variable indicating the second wave (i.e., it is 1 when $t = 2$). $w3_t$ is a dummy variable indicating the third wave (i.e., it is 1 when $t = 3$). X_{it} are control variables that vary over waves and across pharmacies. The control variables included here are the gender of the pharmacist, whether the retail business is a pharmacy or a drugstore, the time of the visit (i.e., before 5 pm or after 5pm), and the type of the request (product-based vs symptom-based). Z_i are control variables that remain constant over waves but vary across pharmacies (e.g., the dummies indicating the sub-city of pharmacy i).

The coefficients in bold identify the DiD effects. Taking the model in Eq. (1), $\boldsymbol{\beta_{c2}}$ identifies the average effect of the coercive letter in wave 2 (compared to wave 1), and $\boldsymbol{\beta_{A2}}$ identifies the average effect of the moral appeal letter in wave 2 (compared to wave 1). Similarly, $\boldsymbol{\beta_{c3}}$ identifies the average effect of the coercive letter in wave 3 (compared to wave 1), and $\boldsymbol{\beta_{S3}}$ identifies the average effect of the sticker in wave 3 (compared to wave 1). Hence, this model assesses the impact of the intervention on the treated groups compared to the control group in the short period (wave 2) and in the relatively longer period (wave 3).

The model in Eq. (2) gauges the impacts of the treatment in each wave in comparison to the previous wave. Hence, in (2), $\boldsymbol{\beta_{c2}}$ identifies the average effect of the coercive letter in wave 2 (compared to wave 1), and $\boldsymbol{\beta_{S3}}$ identifies the effect of the sticker in wave 3 (compared to wave 2). Both models are estimated using the Linear Probability Model (LPM) and we report standard errors clustered at the pharmacy level.

To investigate whether there are differences in how the treatments affect the participants, we conduct a heterogeneity analysis employing background variables (subgroups) that are observable and could be important modifiers of the treatment effects. Specifically, we consider the nature of the retail pharmacy business (pharmacy vs drugstore), the gender of the

pharmacist, the perceived age of the pharmacist (older or younger than 50 years), and the time of the visit (before or after 5pm).

To study the conditional average treatment effect (henceforth ATE) across these various subgroups, we estimate a model by interacting the subgroup characteristics with the treatment indicator variable (Bott et al., 2020). Suppose we want to estimate the conditional ATE of the coercive letter when the visited retail business is a drugstore (rather than a pharmacy). Then we consider the following specification:

$$Y_i = \alpha + \beta C_i + \gamma C_i S_i + +\eta S_i + \theta X_i + \delta Z_i + \epsilon_i \quad \text{.....} \quad (3)$$

where Y_i is the binary variable equal to 1 if pharmacy *i* decided to sell OTC antibiotics, C_i is the treatment indicator for the coercive letter, S_i is the variable upon which the data are partitioned (in our example, it is the indicator variable for pharmacy *i* being a drugstore). The subsample for this analysis therefore includes pharmacies that received the coercive letter and the control group, and it is partitioned into pharmacies and drugstores. As the background variable may be correlated with other characteristics, we include the complete suite of demographic and socioeconomic controls in the above regression. We are mainly interested in γ, the coefficient of the interaction term. With specification (3), the estimated treatment effect of being a drugstore in the coercive letter treatment is $\beta + \gamma$.

We expect the treatments to be less effective on drugstores, old pharmacists, and when visits take place after 5pm. Druggists, as compared to pharmacists, have fewer years of education, less up-to-date professional training, and may therefore lack adequate knowledge about the causes and consequences of antibiotic resistance. Older pharmacists are less likely to be familiar with antibiotic resistance and thus are more likely to hand out non-prescribed antibiotics. In a study on Spanish pharmacists, age is found to be an important variable in explaining the provision of OTC antibiotics (Vazquez-Lago et al., 2017). The time of the visit is also likely to influence treatment effects, particularly for the coercive letter. During the evening and night hours (after 5pm), pharmacists are unlikely to expect auditors to carry out random checks. Moreover, just before closing time, sellers may engage in last-minute sales to increase revenue.

2.4.3 Estimation results

Table 2.2 shows the regression results from models (1) and (2). In line with the descriptive statistics, our DiD specification confirms the large and significant treatment effects. More specifically, the coefficients of the interaction terms between the intervention wave dummy and the three treatment dummies are statistically significant. All three treatments cause a significant reduction in non-prescription sales of antibiotics immediately after the intervention as well as five months later.

Interpreting the DiD coefficients in model (1), in the first follow-up survey (wave 2), the coercive letter has the highest impact of reducing OTC antibiotics by 23.7% compared to the control group. The moral appeal letter reduces the dependent variable by 23.6%. Both the coefficient of $dC_i \times w2_t$ and the coefficient of $dA_i \times w2_t$ are significant at the 1% level. The sticker treatment reduces the illegal sales of antibiotics by 12.2% and the coefficient is significant at 10%. These findings are robust to the inclusion of the observable characteristics. The DiD coefficients for wave 3 indicate that all three interventions continue to have significant effects, despite a decline in magnitude. Five months after the intervention, pharmacies treated with the coercive (moral appeal) letter sell 16.4% (16.5%) less OTC antibiotics compared to the non-treated pharmacies; a sticker on the pharmacy's wall reduces OTC antibiotics by 14.5%. All three coefficients are significant at the 5% level.

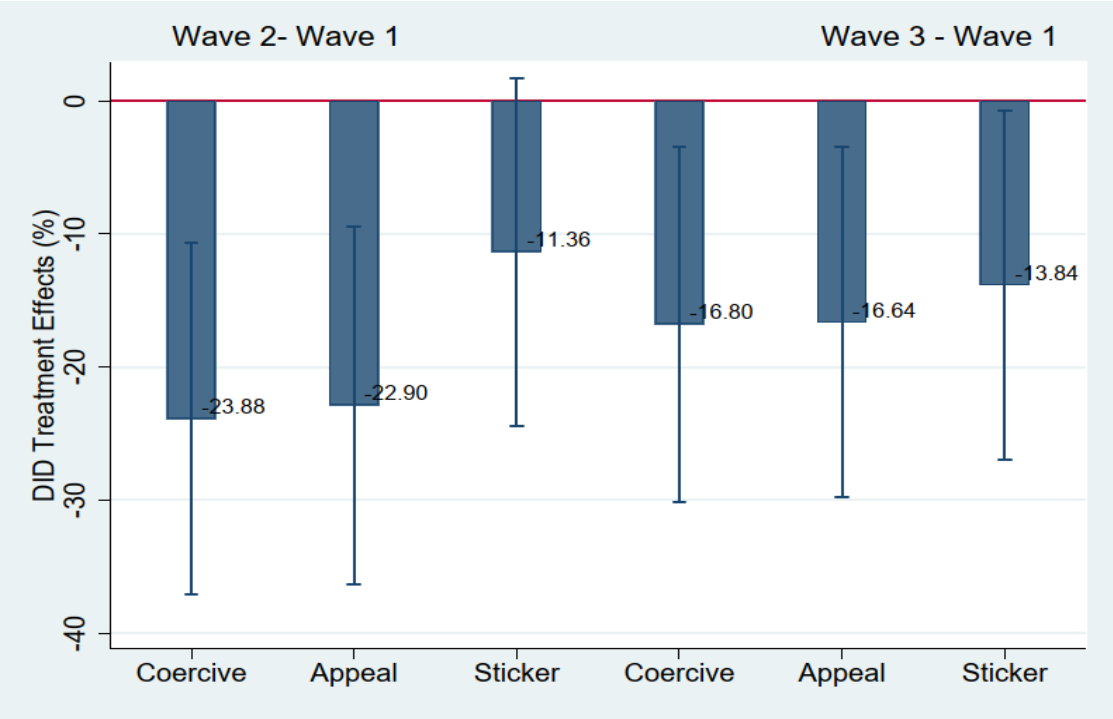
A restrictions test on the coefficients in both the short and long run further suggest that all three nudges are similarly effective in reducing sales of non-prescribed antibiotics. In retrospect the two letters have been interpreted in similar manners by the receivers. This may be since both were issued by the controlling regulatory authority, making the moral appeal letter appear "friendly deterrence". We suspect that the effects might have differed, had the moral appeal letter been issued by an institution such as a professional association or a body of pharmacists. Conversely, the sticker may have served the purpose of a salient nudge for the pharmacist as it was placed on the walls and was constantly under their purview. Additionally, patients walking into a pharmacy treated with the sticker may have been less likely to expect or demand antibiotics from the pharmacists.

Table 2. 2 Treatment effects on OTC antibiotic sales (Extensive margin)

	Model 1	Model 2
dC_i	-0.003	-0.003
	(0.054)	(0.054)
dA_i	0.056	0.056
	(0.053)	(0.053)
dS_i	-0.028	-0.028
	(0.051)	(0.051)
$w2_t$	-0.052	--
	(0.048)	
$w2_t + w3_t$	--	-0.052
		(0.048)
$w3_t$	-0.021	0.031
	(0.048)	(0.044)
$dC_i \times w2_t$	-0.237***	--
	(0.068)	
$dA_i \times w2_t$	-0.236***	--
	(0.066)	
$dS_i \times w2_t$	-0.122*	--
	(0.066)	
$dC_i \times (w2_t + w3_t)$	--	-0.237***
		(0.068)
$dA_i \times (w2_t + w3_t)$	--	-0.236***
		(0.068)
$dS_i \times (w2_t + w3_t)$	--	-0.122*
		(0.066)
$dC_i \times w3_t$	-0.164*	0.072
	(0.068)	(0.061)
$dA_i \times w3_t$	-0.165*	0.070
	(0.067)	(0.061)
$dS_i \times w3_t$	-0.145*	-0.022
	-0.067	(0.062)
Constant	0.735 ***	0.735***
	(0.069)	(0.069)
R-squared	0.09	0.09
Simulated Patient Dummy	YES	YES
Sub-city dummy	YES	YES
Controls	YES	YES
Number of Observations	2,285	2,285
Number of clusters	831	831

Notes: The regressions are based on a linear probability model. The dependent variable is 1 if the pharmacist sold OTC antibiotics. Robust standard errors, clustered at pharmacy level, are shown in parentheses. Sub-city dummies are included with sub-city 1 as the reference category. *** ≤0.01, **≤0.05, *≤0.1

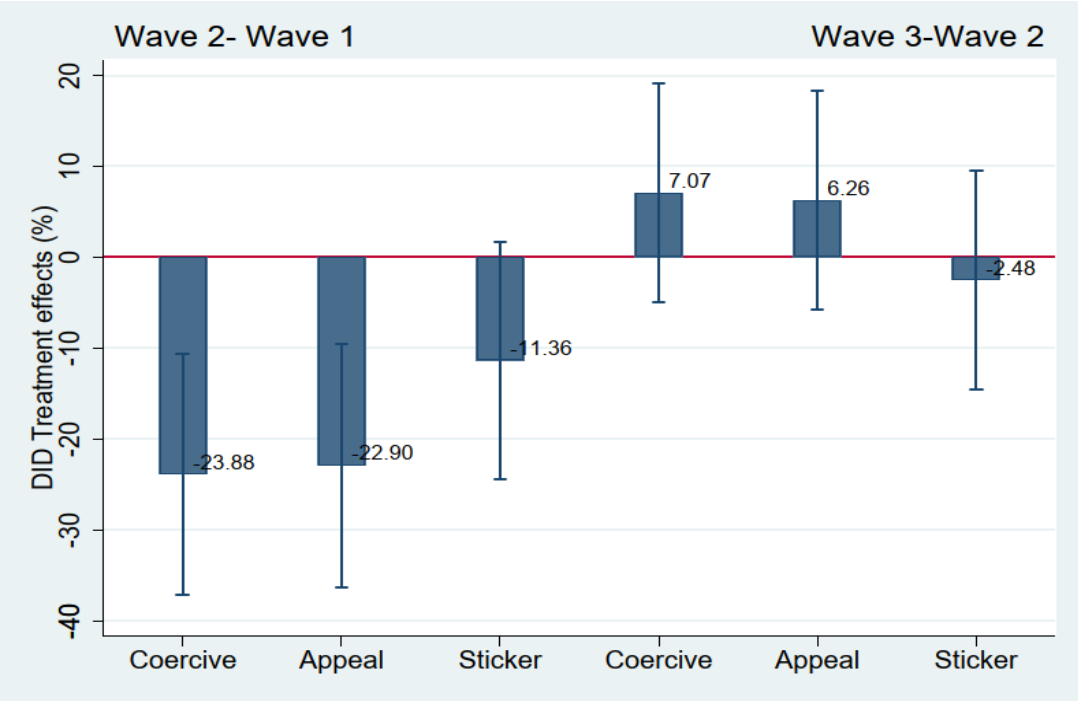
Figure 2. 2 Treatment effects compared to control group.



Notes: The height of each bar represents the estimated coefficients from Eq. (1) (as shown in Table 2.2) and its 95% confidence interval. The graph is indicative of the impact of our treatments in comparison to the control in waves 2 and 3.

Model (2) in Table 2.2 reports the DiD treatment effects based on Eq. (2) and compares wave 2 to wave 1 and wave 3 to wave 2. Focusing on the latter, we note that the coefficients of $dC_i \times w3_t$, $dA_i \times w3_t$, and $dS_i \times w3_t$ (namely, $\boldsymbol{\beta_{c3}}$, $\boldsymbol{\beta_{A3}}$ and $\boldsymbol{\beta_{S3}}$ in Eq. (2)) are not statistically significant, indicating that there is no significant difference between wave 3 and wave 2. The plot of the coefficients and the confidence interval in Figure 2.3 confirm this finding. Although our results are in line with those of previous studies showing that the impact of nudges declines over time, we argue that a 17% reduction for the coercive and moral appeal letter treatments compared to the control group at the fifth month of intervention is a significant achievement at a very minimal cost.

Figure 2. 3 Treatment effects compared to the preceding wave.

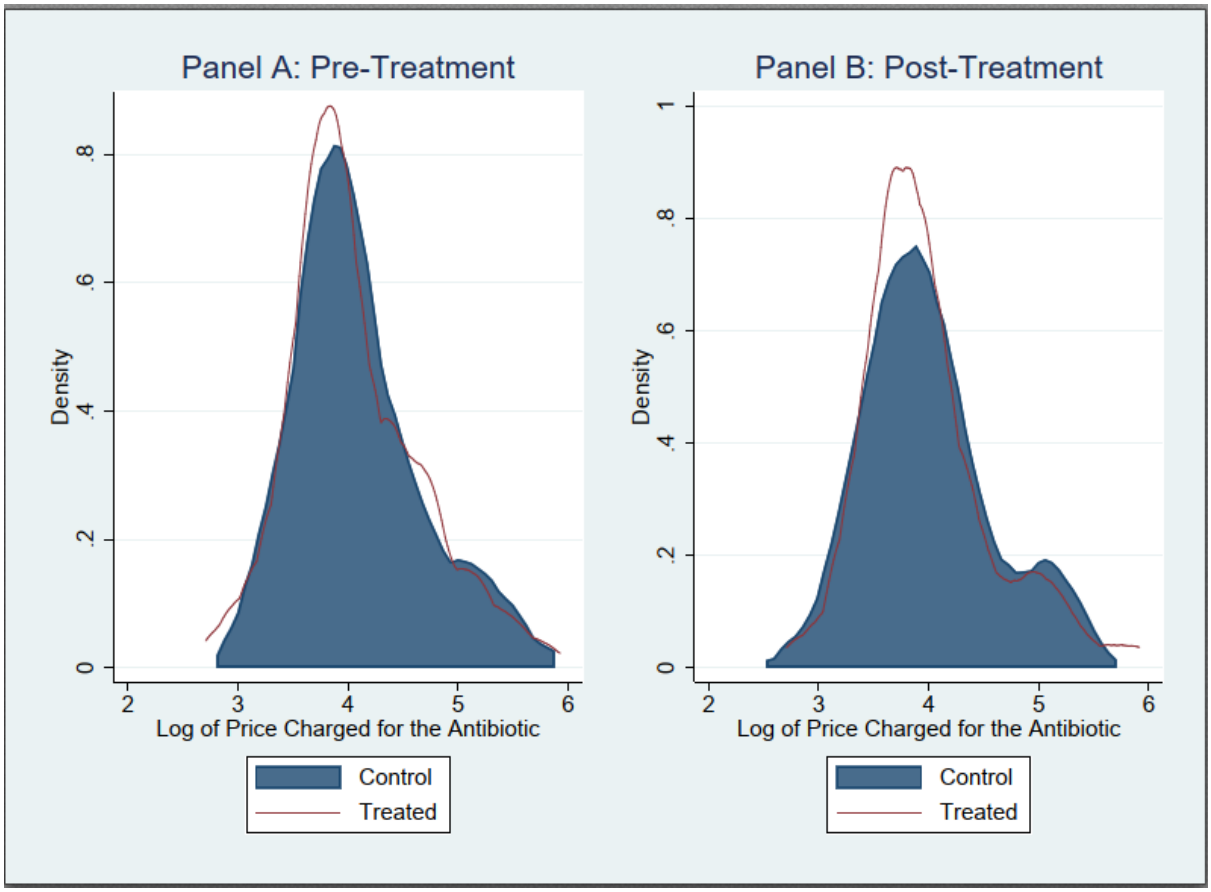


Notes: The height of each bar represents the coefficients from Eq. (2) and column 2 in Table 2.2) and its 95% confidence interval. The graph is indicative of absence of significant differences between wave 2 and wave 3.

We checked for any effects of the treatments on the intensive margin in terms of their effect on the price charged for the antibiotics. Figure 2.4 presents a nonparametric Kernel density estimate of the log of the price charged for OTC antibiotics by the pharmacies before and after treatment. For this analysis we grouped all three treatments into one and display the difference between the treated (all 3 treatments) and the untreated (control) group. The distribution of price pre-treatment (wave 1) and post-treatment (both wave 2 and wave 3) is identical for the groups. There is no significant shift in the distributions post-treatment.

The results are substantiated in Table 2.3 where we set out the results of an OLS regression on the price paid for the antibiotics against the treatment and the control variables in a DiD framework. None of the interaction terms are statistically significant, suggesting that the three treatments do not impact price. However, we find that some control variables are significant determinants of the price charged for the antibiotic. More specifically, female pharmacists (druggists) tend to sell less (more) expensive antibiotics. The specific request made by the patient (UTI vs URTI) is also likely to influence the price charged.

Figure 2. 4 Kernel Density Distribution of Pre- and Post-Treatment for Price Charged



The estimation results of the heterogeneity analysis by subgroup[27] based on Eq. (3) are presented in Table 2.4. The results for each wave and the coercive, moral appeal and sticker treatments are presented in Panels A, B, and C, respectively. The most striking feature of this analysis is that the treatments are successful in reducing non-prescription antibiotics across all groups in both waves: all first-row coefficients are negative, and most are statistically significant. The lack of significance for some subgroups may be due to the smaller sample size. We note that for the coercive letter treatment, particularly for the subgroup "female" and "above 50 years", the treatment effect declines between the two waves. For the moral appeal treatment, this is true for the subgroup "pharmacy" and "female". For the sticker treatment, we note a slight increase in treatment effect for "pharmacy" and "above 50 years".

[27] See Appendix figures **A.2.1 and A.2.2**

Table 2. 3 ATE: price paid for the antibiotic (intensive margin)

	1
dC_i	-8.262
	(7.947)
dA_i	-3.533
	(7.618)
dS_i	1.639
	(8.431)
$w2_t$	-4.921
	(7.426)
$w3_t$	4.599
	(7.479)
$dC_i \times w2_t$	17.790
	(13.075)
$dA_i \times w2_t$	-5.731
	(9.863)
$dS_i \times w2_t$	2.023
	(11.998)
$dC_i \times w3_t$	4.063
	(10.457)
$dA_i \times w3_t$	-4.799
	(10.296)
$dS_i \times w3_t$	-5.033
	(11.594)
Female	-7.536**
	(3.272)
Day (before 5pm)	5.200
	(3.698)
Store	13.416***
	(3.430)
Product (UTI)	14.116***
	(4.680)
Symptom (UTI)	12.930***
	(3.800)
Constant	54.871***
	(7.034)
R-squared	0.048
Simulated Patient Dummy	YES
Sub-city dummy	YES
Number of Observations	980
Number of clusters	586

Notes: OLS regression. The dependent variable is the price paid by the patient. Robust standard errors, clustered at group level, are in parentheses. Sub-city dummies are included with Sub-city 1 as the reference category.
*** ≤0.01, ** ≤0.05

The robust treatment effects are also evident from the low number of significant interaction terms in all three panels. Out of twenty-four interaction terms, only five are significant and display the expected signs. The variable "day" (visit before 5pm) is an important background

variable mediating the impact of our letter treatments. Retail business treated with the coercive and moral appeal letters sold significantly less antibiotics if visited before 5pm compared to the control group. The coercive letter may have a stronger effect during normal working hours, when inspections by the regulatory body auditors are more likely to take place. The heterogeneity analysis across types of sellers (pharmacy vs drugstore) is robust for wave 2; conversely, in wave 3 there are pharmacies supplying OTC antibiotics. Awareness of antibiotic resistance through more years of education does not seem to be an important channel influencing the sales of OTC antibiotics. Older pharmacists (aged above 50 years) treated with the coercive letter have significantly lower sales of OTC antibiotics even after five months. This may indicate that this age group is more risk averse and prefers adhering to the message in the coercive letter. For the sticker treatment, none of the interaction terms are significant.

Table 2. 4 Heterogeneity analysis

	Panel A: Coercive Letter							
	Wave 2				Wave 3			
	Pharmacy	Female	Day	Above 50 years	Pharmacy	Female	Day	Above 50 years
Coercive	-0.347***	-0.266***	-0.078	-0.222***	-0.343***	-0.181**	-0.169*	-0.154***
	-0.089	-0.069	-0.09	-0.051	-0.096	-0.078	-0.099	-0.052
Coercive × group	0.141	0.037	-0.238**	-0.234	0.235**	0.012	-0.007	-0.344**
	-0.108	-0.097	-0.105	-0.144	-0.113	-0.102	-0.115	-0.157
Group	-0.170**	-0.072	0.017	0.087	-0.248***	-0.099	-0.089	0.015
	-0.078	-0.073	-0.079	-0.114	-0.079	-0.074	-0.082	-0.114
Treatment effect on the group	-0.206***	-0.229**	-0.316***	-0.455***	-0.108*	-0.169**	-0.176**	-0.497***
	-0.057	-0.066	-0.055	-0.134	-0.057	-0.063	-0.056	-0.146
Observations	396	396	396	396	396	396	396	396

	Panel B: Appeal Letter							
	Wave 2				Wave 3			
	Pharmacy	Female	Day	Above 50 years	Pharmacy	Female	Day	Above 50 years
Appeal	-0.276***	-0.147*	-0.053	-0.171***	-0.170*	-0.068	-0.065	-0.162***
	-0.084	-0.075	-0.091	-0.051	-0.089	-0.078	-0.106	-0.053
Appeal × Group	0.14	-0.06	-0.178*	-0.104	0.075	-0.097	-0.069	0.348**
	-0.103	-0.1	-0.107	-0.168	-0.107	-0.102	-0.122	-0.143
Group	-0.174**	-0.06	0.021	0.069	-0.233***	-0.034	-0.075	-0.057
	-0.078	-0.074	-0.079	-0.118	-0.079	-0.078	-0.081	-0.11
Treatment effect on the group	-0.136**	-0.207**	-0.230***	-0.274*	-0.101*	-0.165**	-0.138*	0.186
	-0.058	-0.064	-0.056	-0.159	-0.059	-0.064	-0.057	-0.133
Observations	397	397	397	402	400	400	400	396

	Panel C: Sticker							
	Wave 2				Wave 3			
	Pharmacy	Female	Day	Above 50 years	Pharmacy	Female	Day	Above 50 years
Sticker	-0.241***	-0.133*	-0.169*	-0.168***	-0.256***	-0.12	-0.058	-0.182***
	-0.09	-0.077	-0.091	-0.052	-0.096	-0.08	-0.104	-0.052
Sticker × Group	0.131	-0.027	0.028	0.115	0.129	-0.075	-0.14	0.175
	-0.109	-0.101	-0.108	-0.163	-0.114	-0.102	-0.118	-0.154
Group	-0.162**	0.002	0.029	0.078	-0.251***	-0.027	-0.082	-0.023
	-0.078	-0.079	-0.081	-0.113	-0.08	-0.076	-0.083	-0.111
Treatment effect on the group	-0.110*	-0.160**	-0.141**	-0.052	-0.127**	-0.194***	-0.198***	-0.007
	-0.059	-0.065	-0.058	-0.154	-0.057	-0.061	-0.055	-0.143
Observations	396	396	396	396	396	395	395	398

Notes: This table shows the effects on OTC sales of antibiotics of the coercive, appeal, and sticker treatments as well as interactions between the treatment dummy and various background characteristics. The dependent variable is equal to 1 if the pharmacy engaged in OTC antibiotics. Column headers show the indicator variable that is used to define the variable Group, which takes the value 1 if the indicator variable in the heading of the respective column takes the value 1. Pharmacy is equal to 1 if the retail business is operating as a pharmacy as opposed to a drugstore. Female is equal to 1 if the pharmacist serving the simulated patient is female. The day is equal to 1 if the pharmacy/drug store was visited before 5:00 pm. The age variable is based on the SP's perception of the pharmacist's age. Above 50 years is equal to 1 if the pharmacist/druggist is perceived to be 50 or more years old. Panels A, B, and C report estimates for the group of pharmacies that were in the coercive, moral appeal, and sticker treatments, respectively, or in the control. All specifications include sub-city and simulated patient dummies and other controls as in Table 1 and Table 2. The estimates are from an LPM model. Effects are estimated relative to the control group. Robust standard errors in parentheses. *** ≤0.01, **≤0.05, *≤0.1

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2.5 Conclusions

Compliance with good practices in the realm of antibiotics acquisition, storage, disposal, and dispensing is crucial to safeguard public health. This study provides evidence that simple and low-cost nudge interventions are effective in decreasing the amount of OTC antibiotics that are dispensed by pharmacists in Addis Ababa over the medium term (namely at five months from the interventions). Although the treatment effects of the one-time coercive letter (highlighting the legal consequences of OTC antibiotic sales) and the one-time moral appeal letter (emphasizing the pharmacist's key role in the health system) decline over time, they remain statistically significant: compared to the control (untreated) group; pharmacists that received either letter are found to sell significantly less OTC antibiotics even five months after delivery of the letters.

It appears that both economic incentives and moral motivations for not selling OTC antibiotics play a role in shaping pharmacists' behavior. Although our preferred interpretation of the treatment effects of the moral appeal letters is that such letters made the moral argument salient, we cannot rule out other reasons. For instance, it is possible that moral appeal and coercive letters have the same effects on OTC antibiotic sales because the moral appeal letter was issued by AAFMHACA, the controlling regulatory authority in Addis Ababa. This may have caused the recipients to perceive the letter as a threat or pressure from the authority. An interesting line of research in the future would be a repeat of the interventions on the recidivists to check if there are diminishing marginal returns to providing similar interventions to recidivists. Even if beliefs are updated, the treatments might continue to work through the reminder and/or salience channel. The policy would benefit from an inquiry into the nature of sellers that update their beliefs about enforcement permanently.

It has been argued that people become accustomed to a continuous stimulus and consequently their responses to the stimulus tend to decrease over time (see, e.g., Rankin et al., 2009). Our results from the sticker treatment suggest otherwise. We find, in fact, that the sticker – on the pharmacy wall and always in the pharmacists' view – has a persistent effect on OTC antibiotic sales, which does not decline over time. This shows that pharmacists do not get fully accustomed to the sticker even after 5 months. A plausible explanation for the longevity of this treatment is that, unlike the letters, the sticker captures the attention not only of the pharmacists, but also of the customers, thereby offering more leverage to the pharmacists to refuse OTC

antibiotic requests from patients (especially regulars). It would be interesting in the future to remove the sticker from the pharmacy premises and examine whether or not the pharmacists' dispensing behavior returns to pre-treatment levels.

A further noteworthy feature of our study is that the treatments only affect the extensive margin, and have no impact on the intensive margin, i.e., on the price charged by the pharmacists in cases of antibiotics sales. The heterogeneity analysis shows that the effects of the treatments are robust across all subgroups, with very few significant interaction effects between subgroups and treatment: the effectiveness of the letters and the sticker do not depend on the pharmacist's gender, perceived age, the retail business, or time of the visit. As these background variables could have influenced the treatment effects, the robustness of our findings is welcome.

Our study suggests that it is cost-effective for health regulators wishing to curtail the problem of OTC antibiotic sales in low- and middle-income countries to include, in their toolkit, nudge interventions using messages (on letters or stickers) that make salient the consequence of misbehavior, the pharmacist's role in the system, or what the law prescribes. These interventions are, indeed, persistent, and robust to a number of background characteristics.

An interesting line of future inquiry is to utilize the findings on the simulated patient visit to inform the treatment subjects about findings from past random audits. The exact message of the treatment letters could differ on whether the pharmacy was a complier or a defier in a previous visit. Future studies can broaden the realm of nudges that include social norms, social proof and peer comparisons. As per the indication in the letter, actual and real-time auditing of a sub-sample of the pharmacies could throw light on actual behavior and spillover effects on non-audited counterparts.

Although the study site is the capital's biggest urban city, it will be interesting and promising to study a nationwide scale-up of the interventions. Understanding whether such interventions maintain efficacy at scale and outlining the specific mechanisms and pathways could be an area of future research. This study is thus an opportunity to build further evidence on the role of behavioral insights in pharmaceutical regulation.

Appendix 2:

Table A.2.1: OTC Antibiotic Sale by Gender and Age

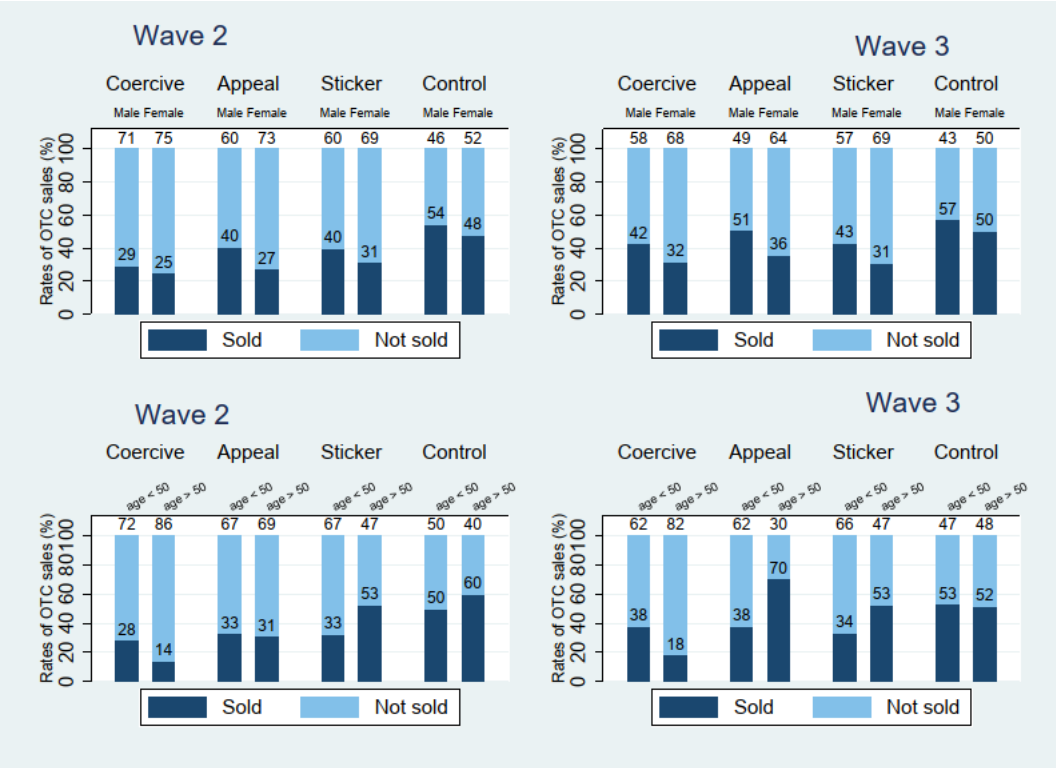
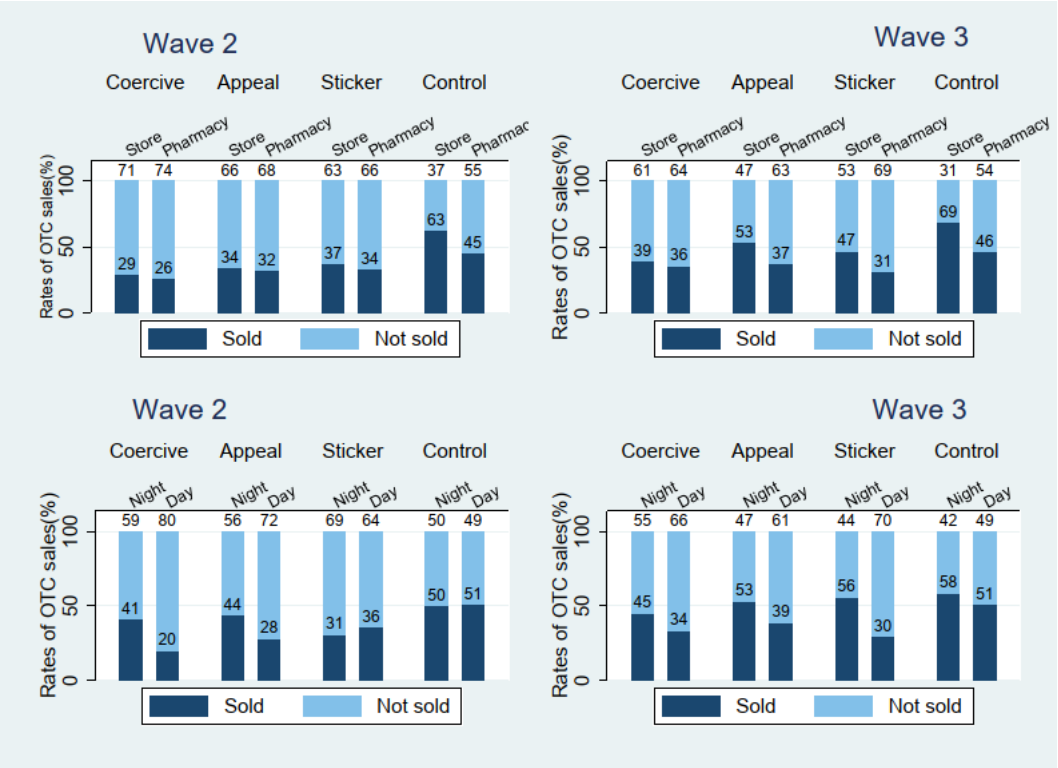


Table A.2.2: OTC Antibiotic Sales by Nature of Business and Time of Visit



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Chapter Three

Inequality of Opportunity in Immunization in Ethiopia: A Shapley Decomposition

3.1. Introduction

Vaccination, since the early 20th century, has been hailed as the most effective intervention in the fight against infectious diseases. Vaccines played a key role in reducing child mortality in recent decades and are found to have a broader impact on the economy by reducing the proportion of households facing catastrophic out-of-pocket health expenses. The use of vaccines helps to avert diseases and results in fewer doctor's appointments, laboratory tests, medications, and hospitalizations, all of which have significant cost savings (Largeron et al., 2015). This is especially the case for low socioeconomic groups which are the hardest hit due to unplanned health expenses (Riumallo-Herl et al., 2018). While vaccine returns vary greatly depending on the type of vaccine, childhood immunization has a high return on investment in low-and middle-income countries[28]. Vaccines can also help in the battle against antibiotic resistance because their primary effect is to reduce or eliminate the risk of infection from antibiotic-resistant strains (Klugman & Black, 2018). Vaccines also minimize antibiotic use by eliminating symptom-based antibiotic prescribing for many common childhood diseases of which fever or diarrhoea is a primary symptom (Lipsitch & Siber, 2016).

Unfortunately, not all children of comparable age groups are able to obtain vaccines and escape Vaccine Preventable Diseases (VPDs). Hence, infectious diseases continue to account for a substantial portion of under-five mortality. Childhood vaccination rates show significant differences between and within countries, with a large section of underprivileged children in developing countries remaining at risk of mortality and morbidity from infectious diseases. The pattern of infectious diseases and incidence of mortality follows the same path[29]. Numerous

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[28] Healthcare costs are reduced by $16–$18 for every $1 spent in immunization against ten major diseases and the net return may be as big as $44 per dollar spent when the broader economic benefits are accounted for (see Liang et al, 2004).

29 In Ethiopia for example, child mortality rates range from as low as 39 per 1,000 live births in Addis Ababa (the capital city) to as high as 125 per 1,000 live births in Afar (see Fenta & Fenta, 2020).

countries around the world continue to fall short of target vaccination rates. It is estimated that close to 19.7 million children in the world received no vaccination or were only partially immunized. Among all children under or unimmunized, 11.7 million live in just ten countries, one of which is Ethiopia[30]. Recent estimates suggest that 1 in 15 children in Ethiopia dies before reaching age 5 mainly due to preventable infectious diseases. Immunization inequality is credited to many factors, none of which contribute equally towards the disparity. It is alleged that geographic monitoring of immunization programs has received more attention than socioeconomic and ethnic disparities in child immunization coverage[31].

Often immunization programs overlook the extent of inequities created by prejudices based on ethnicity, gender, and other such conditions. Outcomes such as income level, educational attainment, and health status are determined by factors outside individual control – called "circumstances" – as well as by factors for which individuals are considered responsible – called "efforts" (Ramos & Van de gaer, 2015). For children and thus for their immunization, access defines "opportunity," because children are not supposed to exert efforts on their own to gain access to essential goods and services (Barros, 2009). Opportunities are said to be unequally distributed if some individuals have an unfair advantage over others due to circumstances beyond their control. This disparity in accessing basic services such as vaccination is formally termed "inequality of opportunity".

According to the Ethiopian Demographic and Health Surveys (DHS) report of 2016, only 22% of children received all basic vaccinations before their first birthday. Disparities in societal and individual determinants are often foundations for inequality in immunization status in early life and health status later in life. Early life health circumstances have been shown to be a vital wellspring for adult life health and productivity (Marmot et al, 2008; Adhvaryu et al., 2019). Children are forced into a downward spiral of misery because they do not obtain timely vaccines, robbing them of their health and future (UNICEF,2016).

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[30] https://www.who.int/news-room/fact-sheets/detail/immunization-coverage

31 See the State of Inequality: Childhood immunization Report by WHO available at: https://www.who.int/docs/default-source/gho-documents/health-equity/state-of-inequality/16-dec-final-for-web-16147-state-of-inequality-in-childhood-immunization.pdf?sfvrsn=ac6c954c_2

These inequalities are socially and economically immoral, and policymakers must address them through a variety of strategy-oriented acts. It is thus crucial to understand the factors that cause and sustain this injustice (Pal, 2015). Moreover, evidence suggests that strategies to eliminate inequalities in opportunities in one's primary years are significantly more cost efficient and efficacious than interventions in adulthood (Barros et al, 2009). In the early years, assessing the extent of inequality and recognizing the causes of these inequalities is a significant first step toward reducing high levels of variation. Tending to such inequality gaps necessitates a deeper understanding of the gaps in immunization coverage.

Using the nationally representative 2011 and 2016 DHS, this study analyzes inequality in immunization opportunities in Ethiopia and sets out to achieve two major objectives. The first is to understand the determinants of child vaccination status in Ethiopia and measure the coverage and inequality. The second objective is to explore how predisposing circumstances like the sex of the child, household characteristics, distance to a health facility, and region contribute to inequality of opportunity in immunization. The determinants of immunization are analyzed using the circumstances of child, household, community, and region-specific characteristics in a logit specification. The study employs the methodology in Barros et al. (2009) to estimate the Human Opportunity Index (HOI) and Dissimilarity Index(D-index) and thus assess changes between the two periods. Furthermore, we employ the Shapley decomposition to measure the role and the contribution several circumstances to inequality, enabling policymakers to target areas that may make the largest contribution to reducing health disparities. More importantly, our study undertakes a regional analysis of the nature of vaccine inequity as country-level vaccine coverage studies tend to disguise regional inequity. Recognizing gaps between sub-groups of the population, such as good and poor performers at regional levels, aids policymakers and planners in understanding programmatic constraints and needs.

Our study reveals that between 2011 and 2016 the overall coverage rate for Ethiopia increased from 24.3 to 37.1 percent with significant regional variations. Addis Ababa (91.3 %) has the highest coverage rate while the lowest coverage rates have been reported in Afar (11.4 %) and Somalia (18.4), both of which are predominantly Muslim and pastoralist regions. To account for the degree of immunization a multinomial logit model of the determinants of immunization was estimated.

The levels of partial immunization coverage in the rural areas were higher than among children in urban areas. The important predictors of complete immunization are birth in a health facility, maternal primary education, mother practicing Christianity, and whether distance to the nearest health facility is considered a problem. The likelihood of full immunization is about 9.1 percent higher for children delivered in health facilities compared to children delivered at home. We find that the HOI increased from 18 per cent to 28.1 percent; the inequality index only showed a marginal improvement, declining by a meagre 2 percent. These improvements are largely appropriated by the urban population as inequality remains constant in rural areas over the study period. The decomposition reveals that regional variations, distance to health facilities, religious affiliations, household economic status and maternal education consistently contribute to inequality.

To the best of our knowledge, no previous study has employed the HOI and DI indices to measure inequality and investigate the share of contributory circumstances to the disparity in immunization in Ethiopia using the Shapley Decomposition. The ability to measure inequality in health and decompose it into its constituent parts has substantial policy consequences. Immunization status and other aspects of early childhood development are largely determined by factors outside a child's control. Predisposing factors such as birthplace, gender, parental education, and wealth are largely beyond the control of children, but they have a significant impact on immunization status and other aspects of their lives. It is thus critical to address such disparities in opportunity because these opportunities influence people's future social and economic profiles. Additionally, targets like the Sustainable Development Goals (SDGs) aim for a significant decrease in maternal, neonatal, and infant mortality, as well as equitable access to sexual and reproductive health services. The SDGs emphasize the importance of immunization in reducing poverty, forming a healthy, more educated, and motivated population. Furthermore, one SDG objective is to reduce inequality in all its forms. Hence, monitoring efforts on a regular basis can reveal whether programs and policies are on track to meet their objectives. To determine patterns, the change in immunization inequality should be tracked overtime. Measuring immunization gaps in health and assessing the scope and determinants of missed opportunities are important first steps in resolving these issues.

The study is organized as follows. Section 2 presents the policy background and profile of immunization in Ethiopia. The conceptual framework for estimating the Logit model and thus

the HOI, the D-Index and the Shapley Decomposition is presented in section 3. Section 4 describes the nature of the data and variables studied. Section 5 presents initial summary statistics and estimation results from a multinomial logit model, the HOI, D-Index and findings from the Shapley Decomposition. The key results and conclusion are presented in section 6.

3.2. Profile and Background of Immunization in Ethiopia

Ethiopia's population is estimated at 112 million (World Bank Indicators, 2019) making it Africa's second most populous country. Ethiopia has made significant strides toward achieving the Millennium Development Goals (MDGs) in terms of health, thanks to consistent implementation of health initiatives. The EPI (Expanded Program on Immunization) which was launched by the Ethiopian government in 1981 with the goal of achieving 100% immunization coverage for all children under the age of two by 1990. While the original goals were updated later, vaccine coverage has generally improved since the inception of the Program, albeit at a suboptimal pace and could have contributed to the overall success of MDGs. However, infectious diseases have a significant contribution the in infant mortality rate, and the country still faces the challenges of providing equal healthcare to a widely scattered, predominantly rural population. Ethiopia has been a Global Alliance for Vaccines and Immunizations (GAVI) priority country since 2002 and is one of ten tier-1 Gavi priority countries with the lowest national coverage for three doses of the combined diphtheria, tetanus toxoid, and pertussis vaccine (DTP3), a widely used performance indicator (Geweniger & Abbas, 2020).

The country's immunization schedule follows WHO recommendations for developing countries. According to the Ministry of Health[32] of Ethiopia a child is considered to have received basic vaccination after receipt of 1-dose BCG[33] (at birth), 3-dose DTP3-HepB-Hib[34] (by 14 weeks), 3-dose polio (by 14 weeks), and 1-dose measles vaccines (by 9 months). Full vaccination includes basic vaccination plus 3-dose pneumococcal conjugate vaccine (PCV) and 2-dose rotavirus vaccines which were only introduced into the national infant immunization

[32] See Ministry of Health Ethiopia https://www.moh.gov.et/ejcc/am/EPI for the recent Routine immunization schedule.
[33] The Bacillus Calmette–Guérin vaccine primary used to protect against Tuberculosis.
[34] The Pentavalent Vaccine is a vaccine that contains five antigens (diphtheria, pertussis, tetanus, and hepatitis B and Haemophilus influenzae type b

programme in November 2011 and October 2012, respectively[35]. While booster doses for childhood immunization are not recommended in routine EPI, periodic supplementary doses for measles, polio, and other antigens are provided via various campaigns with the goal of Reaching Every District (RED) throughout the country.

Despite the government's best efforts, there are gaps in child immunizations due to major structural, cultural, and institutional disparities. National vaccination coverage in general rose from 2011 to 2016, though the number of children who were not vaccinated increased from 14% in 2011 to 16% in 2016 (Bobo & Hayen, 2020). Coverage remains inequitable and remains low across the country, and too many children are never reached by routine immunization. High dropout rates persist between the coverage rates from the first dose to the third dose of DTP. Ethiopia has large numbers of unimmunized children. In 2018[36], 872,828 children were not immunized for the third dose of pentavalent vaccine and 1,215,724 children were not immunized with the first dose of measles vaccines. As a result, ongoing outbreaks of measles have been reported in several years. In addition to the resulting morbidity and mortality, it places a huge economic burden on the health system of the country (Wondimu et al., 2021).

The incidence of unimmunized children (for all basic vaccines given in the country), per 100 children, is highest in Afar (80%) followed by Somali (64%) and Oromia (60%). As a result, Vaccine Preventable Diseases (VPDs) such as tuberculosis, pneumonia, diarrhoea account for most of the under-five mortality. The under-five mortality rate, although on a steep decline compared to the previous decades, is estimated at 55 per 1000 live births. In this setup, it becomes important to study the change in immunization coverage and inequality between 2011 and 2016. It is pertinent to disentangle which circumstances have perpetuated or improved inequality with the goal of designing evidence-based strategies that could help to improve vaccination uptake among the most disadvantaged groups.

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[35] In 2018 and 2019 the government further rolled out the Human Papillomavirus (HPV) and the second dose of the meases vaccine- MCV-2 respectively.
[36] See UNICEF Press release https://www.unicef.org/ethiopia/press-releases/more-870000-children-ethiopia-miss-out-lifesaving-measles-diphtheria-and-tetanus

3.3. Conceptual Framework

Inequality of Opportunity has been on the policy agenda for more than a decade, and research on the subject has become increasingly prominent (Davillas & Jones, 2020). The literature on equality of opportunity dates to the political philosophy discussion in the 1970s and 1980s. Rawls (1971) revived the discussion on equality by gradually moving the "demand for equality" from the realm of individual achievements to the space of opportunities. Rawls emphasized that personal responsibility is an essential qualifier of the kind of equality that is ethically desirable and that opportunities should be available to all people regardless of factors that represent their identity. Roemer (1998) contributed to the debate on determining opportunity-equitable policies and allocation rules. According to Roemer, equality of opportunity is founded on the difference between efforts and circumstances that are within and outside the individual's control. He defines equality of opportunity as a situation where individuals with similar efforts reach similar outcomes, regardless of their circumstances. The main argument here is that health inequalities such as immunization inequality do not happen by chance and are solely determined by circumstances beyond an individuals' control. This school of thought thus overlooks any random variation that may bring about changes in inequality (Checchi and Peragine, 2010).

The inequality of opportunity approach is based on the view that the sources of an individual's desirable outcome, such as good health or high income, are separately due to circumstances and effort. Circumstances are factors that cannot be controlled by an individual, and inequalities emerging from such circumstances should be addressed. Conversely, effort is affected by individual choice and, therefore, inequalities arising from different individual efforts are normatively acceptable. The most important implication is that an equal-opportunity policy should aim to provide everyone with the same opportunity to achieve or enjoy a good outcome. A social planner should seek to equalize opportunities rather than outcomes and allow individuals to be fully responsible for their choices and results.

The Human Opportunity Index (HOI) was developed by the World Bank Group and first presented in 2009 (Barros et al., 2009). The index is inspired by Sen's social welfare function which postulates that a society that targets near universal access to basic opportunities should

increasingly expand basic services to the most disadvantaged groups (Sen, 1976). The study of inequality of opportunity has been employed to study different spheres of human life (Abras et al., 2013; Islam & Mitra, 2015; Pal,2015; Vani & Madheswaran, 2018).

The HOI, which summarizes the equitable availability of services, is an Equity-Sensitive Coverage Rate expressed as the overall coverage rate and a penalty for improperly allocated opportunities (Barros et al., 2009). The HOI is thus best perceived as a coverage rate for a service after discounting the penalty $(P)$for inequality of access. It is a composite indicator of: (i) how many opportunities are available, i.e., the coverage rate of a basic service (denoted by *C*), and (ii) how equitably those opportunities are spread (D-index):

$$HOI = C - P \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

which can be rewritten as:

$$HOI = C\left(1 - \frac{P}{C}\right) = C(1 - D). \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

When using survey data, the procedure entails running a logistic regression model on the full sample for which the HOI measure is constructed to estimate, at an individual level, the relationship between access to a specific opportunity (binary dependent variable) and an individual's circumstances (independent variables).The estimated coefficients of the logistic regression are used to obtain the predicted probability of access to the opportunity for each individual, which is then used to estimate the D-index, the coverage rate. The procedure is developed further below.

The immunization/vaccination status of child i (V_i) is modeled as a nonlinear function of child-specific, household-specific, community-specific, and region-specific characteristics. These represent circumstances in the calculation of the HOI:

$$V_i = \mathrm{F}\ (Child\ specific, household\ specific, community\ specific, region\ specific; \varepsilon_i)$$

The outcome variable V_i is categorised as ‘fully immunised’ if the child has received the full schedule of basic immunization; otherwise as ‘unimmunised’. Thus V_i takes the value 1 if the ith child receives full immunization and zero otherwise. If we generalize the functional form of the above equation, we have:

$$V = X'\beta \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where V is the vaccination status, X is a vector of circumstances and β are the coefficients to be estimated. The probability that a child is fully vaccinated conditional on the explanatory variables is represented as follows:

$$Pr(V = 1|X) = \Lambda(X'\beta) = \frac{e^{X'\beta}}{1 + e^{X'\beta}} \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where Λ represents the cumulative density function of the logistic distribution and is estimated using the method of Maximum Likelihood Estimations (MLE). The marginal effects are computed separately, as coefficients have little meaning and are only indicative of the direction of relationship. Equation (4) will be used to estimate predicted probability $\hat{\boldsymbol{v}}$ (in equation 5) of a child receiving the basic required immunizations given his circumstances which is the basis of the coverage rate in the HOI in Equation (1).

$$\hat{v} = \frac{e^{X'\hat{\beta}}}{1 + e^{X'\hat{\beta}}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Accordingly, we obtain the coverage rate C in Equation (6) using the following computation.

$$C = \sum_{i}^{n} \frac{1}{n} \hat{v} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

The D in Equation (7) is referred to as the Dissimilarity Index (the D-index) and measures the total contribution of all explanatory circumstances to immunization inequality. The D-index can be computed as follows.

$$D = \frac{1}{2C} \sum_{k=1}^{m} s_k |C - C_k| \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

where C is defined as the average coverage rate, s_k represents the share of group k in the population at hand, and C_k is the average coverage rate for group k. According to Barros et al (2009), the D-index is a weighted average of the absolute differences of group-specific coverage rates (C_k) from the overall average access rate, C. The D-index ranges from 0 to 1. A

D-index that is close to 0 implies that access to immunization is relatively independent of the exogenous circumstances. In this situation the HOI is nearly the same as the overall coverage rate C. Alternatively, a D-index that approaches 1 is indicative of a certain social group that is severely excluded from a certain opportunity. There are several group-defining circumstances and hence many probability gaps as there are many possible combinations of group-defining circumstances.

The HOI is Pareto consistent. It improves as the general coverage rate (C) of an opportunity improves without bringing about a change in its distribution among the various groups. A reduction in D, which is an improvement in the way opportunities are distributed, increases the HOI. Thus, policymakers can maximize HOI by improving coverage or ensuring a more equitable distribution of the opportunities. The HOI, however, is a distribution-sensitive index as it gives higher weights to those opportunities assigned to an underprivileged segment of the population than to those allocated to a privileged segment.

After measuring the magnitude of inequality, the next step is to decompose this measure of inequality and attribute the share of contributory factors aka circumstances. Specific techniques for decomposing total inequality into some related component contributions have been adopted in the inequality literature. These techniques broadly fall into two categories. The first considers cases in which the concerned population is divided into different subgroups (see for instance the pioneering articles of Bourguignon, 1979; Shorrocks, 1980; 1984; 1988). The second applies when the targeted variable is the sum of the various components that constitute the source of its value (see Shorrocks, 1982). The recent literature moves in the direction of decomposing inequality based on causal factors.

Expanding on the D-Index, the Shapley decomposition enables estimation of the marginal contribution of each circumstance to inequality in access to immunization. The Shapley decomposition was proposed by Shorrocks (1984) on the premises of the Shapley Value from cooperative game theory. The Shapley Value is an allocation method that designates the gains of a coalition of players among its members as a function of their contribution towards the coalition. The Shapley decomposition has served as a workhorse in distributional studies when an investigation of the relative significance of the explanatory variables is carried out. Drawing parallels, the method is applied to disentangle inequalities by circumstances.

In decomposing inequality, the technique considers the impact on overall inequality of eliminating each circumstance. Because of the absence of an appropriate logical order of elimination, one averages these impacts over all possible sequences of elimination (Sastre & Trannoy, 2002). This is because the circumstances are likely to be correlated with each other and the marginal change in the measure by including one more circumstance depends on the primary circumstances considered initially. To single out the impact of an additional circumstance, one must account for all resulting changes when one circumstance of interest is added to the pre-existing circumstances (Hoyos & Narayan, 2011). This thus warrants taking the average of all such possible changes. The procedure described below produces an exact additive decomposition of the inequality into the total number of circumstances.

The decomposition procedure relies on an important procedure of the D-index, namely that the addition of more circumstances always increases the D-index. Consider two sets of non-overlapping circumstances H and G. Let H and G represent the circumstances that the child was delivered at a health facility and the gender of the child is male, respectively. Then the D-index for both circumstance H and G is greater than the D-index for circumstance H alone i.e. $\mathrm{D(H, G)} > D(H)$. Based on this property, the marginal contribution of circumstance H can be computed as follows:

$$D_H = \sum_{S \subseteq N \setminus \{H\}} \frac{|s|!\,(n - |s| - 1)!}{n!} [D(S \cup \{H\}) - D(S)] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

where N represents the full set of circumstances, which comprises n circumstances; S is a subgroup of N (including s circumstances) that does not encompass the circumstance H; $D(S)$ is the dissimilarity index estimated with the set of circumstances S; $D(S \cup \{H\})$ is the dissimilarity index calculated with set of circumstances S and circumstance H. Once we compute the effect of including circumstance H, the marginal contribution of facility delivery M_H to the immunization dissimilarity index can be obtained as follows:

$$M_H = \frac{D_H}{D(N)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

As per the property of the Shapley decomposition, the total of all circumstances' contributions amounts to 100 per cent i.e $\sum_{i \in N} M_i = 1$. The computations of the HOI, the D-index and its

consequent decomposition were undertaken in STATA following the procedure by Juárez & Soloaga (2014).

3.4. Data Source, Description of Variables and Summary

The data source for this study is the 2011 and the 2016 nationally representative Demographic and Health Survey (DHS)[37]. The DHS programme collects nationally representative data on population health in low- and middle-income countries as part of the global DHS project. These surveys are the third and fourth comprehensive surveys conducted in Ethiopia. Samples in the two surveys were selected using a stratified, two-stage cluster design. Enumeration Areas (EAs), in which the smallest administrative unit of the country are divided into small units, were the sampling units for the first stage. Households comprised the second stage of sampling. The target groups in the household were all women aged 15-49 and all men aged 15-59 who were either permanent residents of the selected households or visitors who stayed in the household the night before the survey. The 2011 survey contains detailed background information from 18,500 households, 16,515 female, and 14110 males; in 2016, these numbers are 16,650, 15,683, and 12,688, respectively.

The surveys are designed to provide up-to-date estimates of key demographic and health indicators for the country and involve urban and rural areas of the nine regions, and the two administrative cities of the country. The background information includes immunization[38] details of children aged 12-23 months. Mothers were asked whether they had a vaccination card for each child. If the card was available, the details of vaccinations were taken from the card. If the details were not present on the card, then records of health facilities and the mother's recall was used. If the mother could not show a vaccination card, the mother's recall on the vaccinations received was used.

[37] Datasets available for free upon request, see https://dhsprogram.com/

[38] To enable comparison with DHS 2011, we only considered routine immunization covered in both surveys, although the 2016 survey also included information on the newly introduced vaccines of Rotavirus and PCV.

The first step in building the inequality index and its composition is to identify and create the right circumstances that are exogenous and exert influence on access to immunization. We explored the literature on the enablers and barriers to immunization. Studies for other countries such as India (Patra, 2008) and Ghana (Asuman et al., 2018) have found considerable variability in childhood vaccination associated with several factors. Vaccination coverage is determined by a complex mix of demographic, structural, social, and behavioural factors (Thomson, Robinson & Vallée-Tourangeau, 2016). The DHS surveys include a range of predictor variables that can be grouped into child-specific, mother- (household-) specific, community-specific and region-specific factors. The child-specific variables include gender and place of birth/facility delivery etc. The household-specific factors include the mother's age when giving birth, schooling, religion, the household's socioeconomic status, and whether the family has access to media. One of the community-specific factors considered is whether the population is rural or urban. In addition, the data included whether the distance to the community's nearest health center was a problem for the household. We considered all these factors in our analysis. Following the vaccine literature, our research focuses on basic vaccination for children aged 12 to 23 months at the time of the survey (see Geweniger & Abbas, 2020; Pal, 2015). As previously mentioned, for the purposes of comparison we use the 2011 and 2016 DHS survey.

Several factors have been identified as having an influence on child immunization coverage. The child-specific, mother-specific, community-specific, and region-specific factors that are considered important predictors of immunization were extracted from the immunization literature.

Gender – Global immunization data is not indicative of a significant difference in immunization outcomes between boys and girls. However, in some countries like South Asia there is evidence that in communities with a strong inclination for sons, female children are relatively less likely to be immunized (Prusty & Kumar, 2014). Gender may thus influence child immunization outcomes, although there is a knowledge gap in this field.

Place of delivery – The mother's subsequent health-seeking behaviour for herself and her infant is influenced by whether the child was born at home traditionally or in a health facility with the assistance of professional birth attendants. So far, data show that missed immunization

opportunities are more common with home deliveries (Moyer et al., 2013; Aggarwal et al., 2010).

Mother's age – The association between maternal age and preschool immunization coverage is not clear-cut (Salmon et al., 2009). On the one hand, some studies have indicated that children of younger mothers are at increased risk of under-immunization. On the other hand, younger mothers are found to have more fully immunized children, presumably because they have less children and can devote more time and attention to them. However, as she grows older and has more children, other children are likely to compete for her time and attention. "Immunization fatigue" may set in as the number of children increases (Adedokun et al., 2017). The other point is that as mothers get older, they gain more experience in child rearing and learn about children's health and upbringing in general.

Mother's employment status – The literature suggests that as women earn more income, they are more likely than men to spend their income on food, education, healthcare, and other family needs. Women who earn an income are likely to pay for medical services as well as incur transport costs to access them (Balogun et al., 2017; Burroway & Hargrove, 2018; Özer et al., 2018), and regardless of their education level, employed women are more likely to vaccinate their children. Women, as compared to men, are presumed to have stronger preferences for children's wellbeing and hence any increase in their financial share is likely spent on enhancing children's welfare (De Hoop et al., 2017). Working mothers are more likely than unemployed mothers to have their children immunized, and this has been attributed to maternal employment reducing financial barriers to vaccination, particularly if these barriers include money and transportation (Bates & Wolinsky, 1998). Another mechanism at play is that working women may have greater decision-making power and ensure that their children receive full immunization when their spouse does not significant contribute to household living expenses.

Maternal Education – As parents' educational attainment increases, the likelihood of being unimmunized decreases. Educated mothers are likely to be more confident and communicative, making relationships with healthcare providers more easily and increasing their children's immunization rates. Educated mothers are often more likely to stick to their immunization schedules, ensuring timely vaccination and lower dropout rates (Vikram et al., 2012; Forshaw et al., 2017). Maternal education is particularly important as it operates via the income channel explained above.

Household wealth – Household wealth, measured as a composite index of household assets, displays a gradient pattern, with lower levels of coverage in poor households. This is a common finding for most developing countries. According to WHO (2012), in Afghanistan other things being equal, the odds of coverage were 2.7 times greater for children in the richest quintile than in the poorest quintile.

Religion – The type of religion practiced in the household usually by the mother may have a significant impact on maternal and child health. It has been shown that Muslim-majority countries have higher maternal and infant mortality rates, as well as poorer coverage of reproductive, maternal, baby, and child health interventions **(**Akseer et al., 2018; Costa et al., 2020).

Media access – Access to Media has proved to be an important arsenal in combatting rising vaccine hesitancy and increasing vaccine awareness. Media exposure can help to communicate the benefits of immunization, handling the side effects of the jab, and clarifying vaccine misinformation.

Place of residence – This refers to the household location either in a rural or urban area. Inequities in immunization coverage between rural and urban areas are inextricably connected to both supply- and demand-related factors for childhood immunization (Antai, 2011). A household location in an urban area indicates better health services, as well as possibly better paternal education and earnings. Many studies indicate that living in rural areas has an inverse association with completing immunization doses on time. Conversely, Asuman et al. (2018) find that children in rural areas are more likely to complete mandatory vaccines and suggests that this may be due to large-scale government programs focusing on rural areas. In urban areas, there is also a scarcity of immunization services tailored to vulnerable communities including slum dwellers, street children, and newly displaced migrants.

Distance to the nearest health center – While the above factors can be attributed to demand side factors influencing vaccine demand, supply side factors such as distance to the recent health center may play a key role in facilitating the convenience and affordability of vaccine services. Although immunization services are free in government health centers, we may be able to capture the cost of transport and the time taken. The distance between a person's home and a healthcare facility has been shown to be strongly associated with vaccine uptake.

Region/State specific factors – Vaccinations are administered locally by health officers with the assistance of authorities at higher regional levels in an organizational hierarchy. In regions with a large rural population and a significant nomadic population, the failure of health officers to track and follow pastoralist families in their way of life has resulted in lower immunization outcomes. Regional differences may be explained in part by the way of life, resource endowments or infrastructural resources (Abebe et al., 2012).

For ease of analysis, we have classified the above explanatory circumstances into child-, household-, community-, and region-specific circumstances, as shown in Table 3.1.

Table 3. 1 Description of the Circumstance variables

Circumstance	Description	Type
Female	=1 if Child is female; 0 otherwise	Child specific
Place of Delivery	=1 if Child is Delivered in a health facility; 0 otherwise	Child specific
Mother's age	Mother's age in years at time of the child's birth	Household specific
Employed	=1 if Mother is employed; 0 otherwise	Household specific
Primary education	=1 if Mother has primary education; 0 otherwise	Household specific
Secondary education	=1 if Mother has secondary education; 0 otherwise	Household specific
Tertiary education	=1 if Mother has Tertiary education; 0 otherwise	Household specific
Christian	=1 if Mother practices Christianity; 0 otherwise[39]	Household specific
Middle income	=1 if household is classified as middle income; 0 otherwise	Household specific
Rich	=1 if household is classified as rich; 0 otherwise	Household specific
Media access	=1 if household has access to media; 0 otherwise	Household specific
Distance is a problem	=1 if household perceives that distance to the nearest health center is a problem; 0 otherwise	Household specific
Urban	=1 if place/community household belongs is classified 1 if urban; 0 otherwise	Community specific
Region	11 dummies representing the nine regions and two administrative cities	Region specific

3.5. Results

3.5.1 Descriptive Results

The summary statistics of the variables utilized for the empirical analysis are presented in Table 3.2. In general, we note that vaccine coverage has improved over the two periods in the various dimensions under consideration. For the urban population, for example, coverage increased

[39] Christian includes all denominations of Orthodox, Catholic and Protestant Christians. Muslim and other traditional religions are grouped together.

from 48.1 percent in 2011 to 65 percent in 2016. The same figure for the rural population stood at 20.3 percent and 35 percent respectively. Not surprisingly, coverage is high for BCG, first dose of DPT and polio after which it gradually declines, indicating dropout rates from the routine immunization program. Coverage has increased for both male and female children.

Despite the expansion of the supply of maternal health services through health extension workers by the government and a marginal increase in rates of delivery in a health facility, home birth is common in Ethiopia. While 54 percent of children born in a health facility in 2016 received all basic vaccinations, this proportion is only 30 percent for home deliveries. Regarding education, 57.7 percent of the children of mothers with secondary and higher education were fully vaccinated while only 20 percent of the children of illiterate mothers were fully vaccinated. Regarding religious affiliation, while fully vaccinated children increased by nearly 20% between 2011 and 2016 for children born to Christian mothers, it only increased by 11% for children born to Muslim mothers. The descriptive statistics also indicate that having health insurance and having a vaccination card are positively associated with completing the full doses of immunization[40]. The regional profile of immunization coverage is presented in Table 3.3. Coverage increased over the two periods in all the regions with disparities from location to location. Addis Ababa has the highest coverage rate, followed by Dire Dawa and Tigray. The lowest coverage rates were reported in Afar and Somalia, both of which are predominantly Muslim and pastoralist regions.

[40] Having health insurance and a vaccination card are not part of the logit model

Table 3. 2 Coverage of vaccinations across circumstance variables in 2011 and 2016

	All basic vaccination		BCG		DPT/Pentavalent		Polio		Measles	
Circumstances	**2011**	**2016**	**2011**	**2016**	**2011**	**2016**	**2011**	**2016**	**2011**	**2016**
Residence	48.1	65	81.6	89	62	80	67	80	79.6	76
Urban										
Rural	20.3	35	63.8	67	32.9	50	41.5	54	51.7	52
Gender										
Male	23	36	64.2	69	34.9	53	43	57	55.8	73
Female	25.7	40	68.6	69	39.4	53	47.5	57	55.6	56
Birth Order										
First birth	29.6	47	71.4	72	41.1	59	47.9	60	60.6	59
Second birth	24.2	45	68.6	78	37.6	63	44	64	52.6	64
Third birth	22.3	41	62.9	70	35.2	54	44.9	59	55.9	52
Forth and more births	238	33	64.2	66	35.8	48	58.2	52	60.8	51
Place of Delivery										
Home	20.5	30	63	63	33	44	42.3	48	51.6	48
Health facility	53.1	54	87.9	80	67.8	69	65.8	71	82.7	65
Post-natal check up										
No check up	20.3	36.5	62.7	68.6	32.1	50.8	42.4	54.5	52.5	51.8
Check up	31.1	63.4	78.9	79	56.1	79.1	45.9	81	62.9	85.1
Mother's Education										
No education	20	31	60.1	64	31.7	45	40.8	50	49.9	49
Primary	28.5	46	75.3	73	43.8	62	49.9	65	63.5	59
Secondary	57	70	99.8	84	79.2	80	77.9	78	82.1	78
Higher	57.7	72	99.4	94	64	79	73	79	99.5	80
Mother's religion										
Muslim	16.4	27	60	59	28	42	35.1	46	46.7	44
Christian	28.6	48	69.8	76	42.1	62	50.5	65	60.4	62
Media access										
No access	22.4	36.5	64.7	68	35.1	51.5	43.9	55	53.2	52.7
With access	52.2	83.7	89.2	96.2	66.3	90.3	62.3	89.6	90.1	90.5
Mother's employment										
Not employed	25.4	36.7	66.1	67.3	37.5	50.6	43.7	53.7	55.1	52.7
Employed	22.6	42.9	66.7	73.7	36.7	59.3	47.5	63.2	56.7	58.2
Health Insurance										
No insurance	24.4	37.4	66.3	68.6	37.2	52.2	45	19.6	55.6	53.6
With insurance	1.7	65	95.3	82-8	2.7	76.2	90.8	23.8	95.3	71.5
Vaccination card										
No card	11.2	41.6	57.5	3.5	20.5	13	33.6	19.5	47.3	29.1
With card	57.4	86.2	88.7	54.5	79.1	77.3	74.2	76.2	76.7	62.9
Distance Problem										
No problem	37.4	48.2	74.4	76.9	50	63.7	56.9	67.9	71.9	63.2
Yes problem	19.4	32.1	63.3	64	32.3	46.1	40.7	48.8	49.7	48.4
Economic status										
Poor	17.4	29	61.9	61	27.6	43	39.1	48	48.6	46
Middle income	18.2	36	61.5	69	31.6	51	51.9	57	51.5	54
Rich	36.9	53	74.8	80	52.6	69	54.6	68	67.1	66

Source: Calculation based on DHS 2011 and 2016

Table 3. 3 Coverage of vaccinations across regions in 2011 and 2016

Circumstances	All basic vaccination		BCG		DPT/Pentavalent		Polio		Measles	
	2011	2016	2011	2016	2011	2016	2011	2016	2011	2016
Region										
1. Tigray	58.9	67	95.9	88	74.3	81	76.4	79	83.7	80
2. Afar	8.6	15	37.2	44	11.6	20	20	36	29.9	30
3. Amhara	26.5	46	68.3	75	39.8	64	48.7	67	62.1	62
4.Oromia	15.7	25	57.1	60	27.3	40	36.3	43	45.8	43
5. Somali	15.6	22	45	56	24.9	36	29.1	44	38.7	48
6.Benishangul	23.7	57	69.1	77	43.1	76	45.9	70	67.6	71
7.SNNPR	23.8	47	73.3	76	38.2	59	47.3	64	57.7	58
8. Gambela	15.5	41	72	70	29.7	55	43.9	58	51.7	62
9. Harari	34.1	42	73	77	54.4	59	62.3	79	64.7	54
10. Addis Adaba	78.7	89	97.5	95	89.2	96	81.7	97	93.5	93
11. Dire Dawa	58.3	76	87.4	97	89.3	85	80.9	82	80.3	87

Source: Calculation based on DHS 2011 and 2016

3.5.2 Results on Determinants, HOI, D-Index and Shapley Decomposition

The estimation of the dissimilarity index and the share of the various factors that contribute to the dissimilarity (Shapley decomposition) rely on the dichotomous nature of the opportunity under consideration in a logit estimation framework. The use of the logit model masks the degree of immunization as there is a great difference between partially immunized child and a child who received no immunization. To account for differences in the degree of immunization, we chose to present results from a multinomial logit specification to probe into the determinants of immunization. Our outcome variable is thus grouped as (1) non-immunized (base category), (2) partially immunized and (3) fully immunized. Non-immunized was defined as children who did not receive any of the recommended vaccines. Partially immunized was classified as children who received at least one but did not achieve all the recommended vaccines. Fully immunized was defined as children who received all recommended basic vaccines. The multinomial model was estimated using the independent variables or the circumstances as described in Table 3.1 above.

Table 3. 4 Multinomial Logit analysis of not immunized, partially immunized, and fully immunized for 2011

Omitted category=Not immunized						
	National		Urban		Rural	
	Partially immunized	Fully immunized	Partially immunized	Fully immunized	Partially immunized	Fully immunized
Female	1.026	1.068	2.336	3.460	0.974	0.945
	(0.165)	(0.182)	(2.276)	(3.222)	(0.160)	(0.174)
Health facility	1.697	1.971	1.015	0.878	2.088	2.567*
	(0.818)	(1.080)	(0.597)	(0.562)	(1.061)	(1.311)
Mother age	1.011	1.031**	0.974	1.007	1.014	1.033**
	(0.013)	(0.015)	(0.040)	(0.038)	(0.014)	(0.016)
Employed	0.951	0.910	0.696	0.901	1.003	0.948
	(0.189)	(0.206)	(0.346)	(0.535)	(0.209)	(0.225)
Primary education	2.067***	2.557***	3.788***	7.886***	1.940***	2.250***
	(0.401)	(0.592)	(1.688)	(4.190)	(0.386)	(0.560)
Secondary education	10.24***	11.855***	6.262**	13.095***	571.967***	796.063***
	(8.440)	(10.754)	(5.602)	(12.348)	(641.511)	(1,039.481)
Tertiary education	0.810	0.988	22.978***	44.243***	0.198	0.326
	(0.759)	(0.911)	(17.803)	(42.432)	(0.213)	(0.353)
Christian	0.687	0.952	0.350**	0.417	0.682	0.958
	(0.199)	(0.297)	(0.182)	(0.238)	(0.205)	(0.324)
Middle income	0.942	1.053	0.828	0.002**	0.950	1.074
	(0.190)	(0.251)	(1.038)	(0.000)	(0.198)	(0.266)
Rich	0.956	1.415	0.697	3.824	1.022	1.544*
	(0.191)	(0.342)	(0.380)	(3.330)	(0.219)	(0.399)
Media access	0.860	1.696			0.727	1.135
	(0.451)	(0.961)			(0.402)	(0.815)
Distance problem	0.658	0.449***	1.234	0.611	0.669	0.521**
	(0.168)	(0.116)	(0.489)	(0.252)	(0.176)	(0.141)
Urban	1.209	1.542				
	(0.481)	(0.765)				
Region dummy	Yes		Yes		Yes	
Observations	3,703		692		3,011	

***Notes**:* The estimated parameter represent the relative risk ratios. Values below one indicates smaller chance of belonging to group, values above one higher chance, relative to the omitted category which is not immunized. Standard errors in parentheses. Regional dummies are included with Tigray as a base region. *** p<0.01, ** p<0.05, * p<0.1 In the urban multinomial logit regression, medical access is omitted because of the sparse nature of the variable.

Source: Estimation based on DHS 2011

Table 3. 5 Multinomial Logit analysis of not immunized, partially immunized, and fully immunized for 2016

	Omitted category=Not immunized					
	National		Urban		Rural	
	Partially immunized	Fully immunized	Partially immunized	Fully immunized	Partially immunized	Fully immunized
Female	0.960	0.904	0.173**	0.276*	0.996	0.900
	(0.123)	(0.142)	(0.126)	(0.204)	(0.130)	(0.148)
Health facility	1.080	1.683*	1.476	3.884*	1.089	1.695
	(0.319)	(0.521)	(1.008)	(2.678)	(0.332)	(0.548)
Mother age	1.005	1.002	0.995	0.969	1.005	1.002
	(0.014)	(0.015)	(0.063)	(0.054)	(0.014)	(0.015)
Employed	1.136	1.412	4.383*	3.262	1.094	1.477
	(0.245)	(0.341)	(3.499)	(2.349)	(0.245)	(0.375)
Primary education	1.332	1.915***	1.136	7.525**	1.348	1.793***
	(0.280)	(0.379)	(1.119)	(7.292)	(0.287)	(0.357)
Secondary education	0.789	1.452	0.047**	1.264*	1.790	3.183*
	(0.440)	(0.792)	(0.038)	(0.490)	(1.145)	(2.183)
Tertiary education	0.190**	0.522	0.070***	0.846	0.079***	0.067**
	(0.154)	(0.388)	(0.061)	(0.711)	(0.065)	(0.073)
Christian	1.284	1.977**	0.660	0.867	1.303	1.998**
	(0.320)	(0.537)	(0.527)	(0.695)	(0.332)	(0.566)
Middle income	1.821***	2.038***	16.402*	15.077	1.875***	2.073***
	(0.397)	(0.465)	(27.520)	(27.598)	(0.416)	(0.484)
Rich	1.393	2.002***	2.433	2.176	1.393	1.964***
	(0.312)	(0.462)	(2.083)	(1.965)	(0.318)	(0.468)
Media access	7.186***	10.434***	0.933	1.682	98.293***	103.622***
	(4.402)	(7.048)	(.825)	(1.27)	(122.635)	(129.664)
Distance problem	0.828	0.665**	0.135***	0.162**	0.866	0.669*
	(0.143)	(0.134)	(0.102)	(0.114)	(0.152)	(0.139)
Urban	3.834***	2.163				
	(1.782)	(1.202)				
Region dummy	Yes		Yes		Yes	
Observations	3,604		726		2,878	

***Notes**:* The estimated parameter represent the relative risk ratios. Values below one indicates smaller chance of belonging to group, values above one higher chance, relative to the omitted category which is not immunized. Standard errors in parentheses. Regional dummies are included with Tigray as a base region. *** p<0.01, ** p<0.05, * p<0.1

Source: Estimation based on DHS 2016

Tables 3.4 and 3.5 present the relative risk ratio from the multinomial logit regressions for the years 2011 and 2016 for the whole country, rural and urban areas separately[41]. Estimated

[41] Since the HOI and Shapley decomposition is based on the logit regression model, estimation from the logit model is presented model in table appendix A.3.1. Our results are largely comparable.

parameters are presented as relative risk ratios. Parameters greater than one indicate the regressor is associated with a probability of the outcome that is greater than the probability of the base case (not immunized), everything else equal. Parameters below one indicates that the variable is causing the outcome to have a smaller probability than the base case.

For both 2011 and 2016 mother's age, mother's primary education, household wealth, and distance to the nearest health centre are important predictors of complete immunization. Education of mothers increase the predicted probability of partial immunization, compared to non-immunization. The variable media access increases the predicted probability of immunization, compared to non-immunization for the year 2016. The regression results for 2016 also indicate that females are less likely to be immunized in the urban regions. Regarding the regional dummies, we find that they are significant predictors of immunization in both periods. A child residing in Tigray has a higher probability of being immunized than a child in any other region except Addis Ababa, Beninshangul Gumz and Dire Dawa.

As a next step to estimate inequality of opportunity we employ the predicted probabilities from a logit model as explained in section 3.3. We estimate inequality of opportunity in Ethiopian childhood immunization for the years 2011 and 2016[42]. Inequality of opportunity in immunization is shown in Figure 3.1. The graph shows the change in opportunity of inequality over the five-year period. The X-axis indicates the percentile groups of children after ranking them based on the predicted probability of full immunization from the logit estimation. The Y-axis indicates the predicted probability of full immunization for each percentile group.

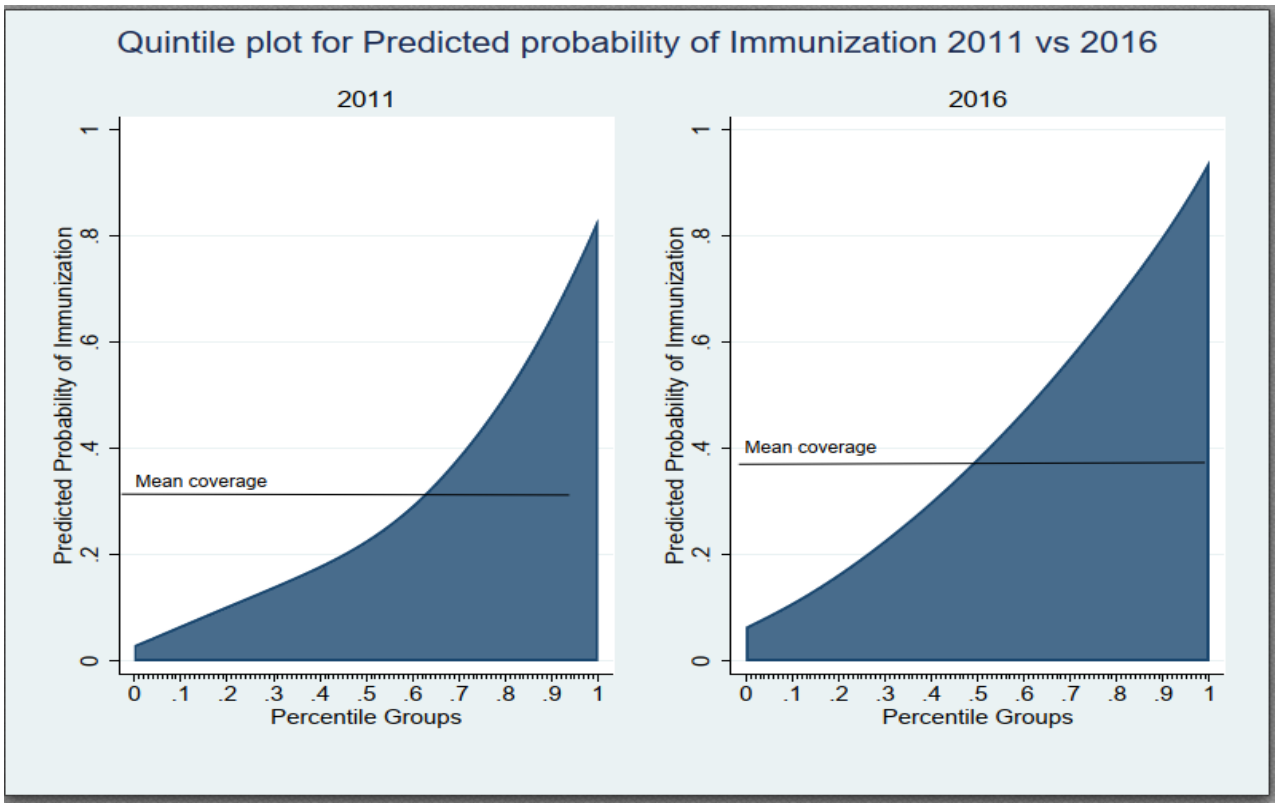
The triangular region above the coverage rate is indicative of the magnitude of inequality as it amounts to immunization opportunities that are unequally distributed within the population. Figure 3.1 suggests that inequality of opportunity in immunization is not significantly different over the five-year mark. Dissimilarity Index calculations in Table 3.5 confirm our visual findings. The dissimilarity index for Ethiopia marginally decreased from 25.4 to 23.4. Despite the marginal improvement in the dissimilarity Index, Ethiopia's HOI in immunization improved from 18 percent in 2011 to 28.4 percent in 2016. This is attributed to significant gains

[42] In tables A.3.2- A.3.5 coverage rates, the dissimilarity index and corresponding share of the circumstances to the dissimilarity index were also estimated for the non -immunized vs partially immunized and the non-immunized vs the fully immunized.

in coverage. Except for Harari, all other regions gained on account of HOI in immunization over the study period. The HOI is lowest in the Afar and Somali regions which are predominantly pastoralist and pursue a nomadic lifestyle. These findings are visualized in Figure 3.2, which illustrates the dissimilarity index and the HOI by region.

On a rural-urban disaggregation, our study confirms that while the inequality index for urban children waned from 24 percent to 19 percent, it did not change for children residing in rural areas. The disaggregation at the regional level confirms that inequality of opportunity worsened for the group of children residing in Amhara, Harari and Dire Dawa.

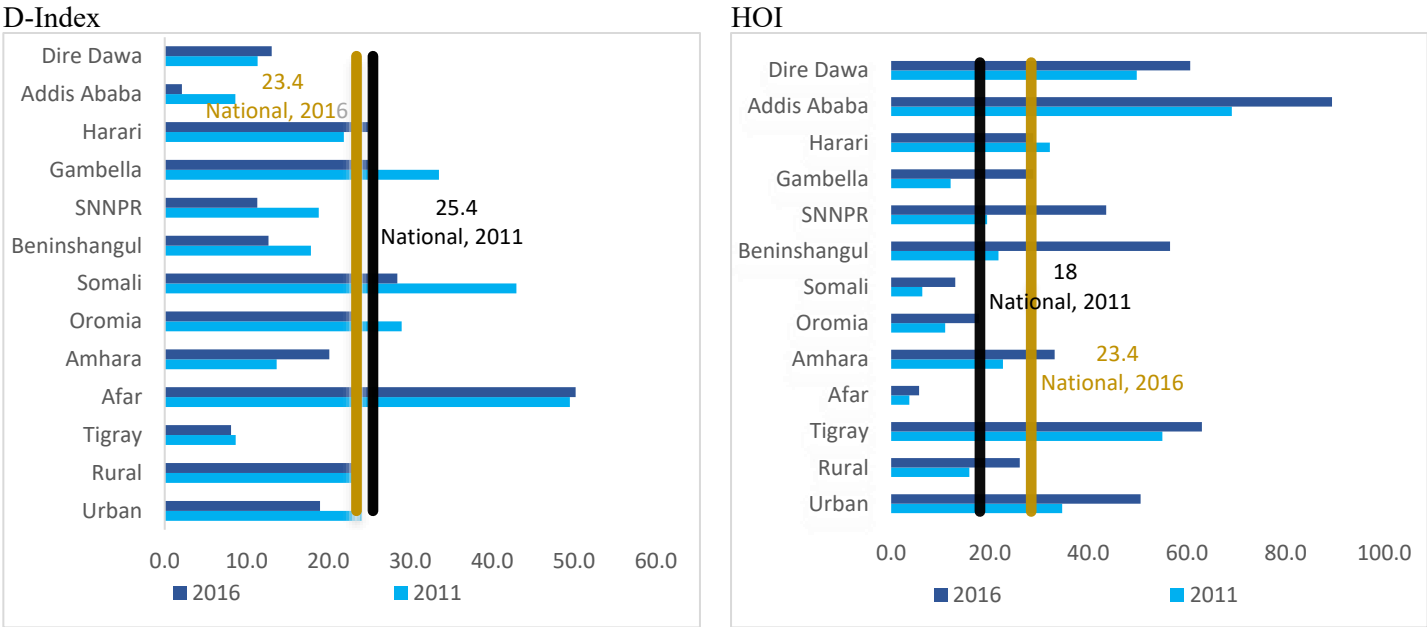
Figure 3. 1 Quantile Plot for the Probability of Getting Basic Vaccination: 2011 vs 2016.



Source: Own calculation based on DHS 2011 and 2016

The largest increase was noted for the Amhara region from 13.7 percent in 2011 to 20.1 percent in 2016. The dissimilarity index did not show big differences for Afar over the study period. The relatively large gains in the dissimilarity index for Somali, Gambela, SNNPR, and Addis Ababa are noteworthy. In the following part of the results, we discuss the contribution of the various circumstances to the dissimilarity index through the lens of the Shapley Decomposition.

Figure 3. 2 D-index and HOI Across the Regions



Source: Own calculation based on DHS 2011 and 2016

Table 3. 6 Coverage, Dissimilarity, HOI index at national, regional level and by place of residence

	2011			2016		
	Coverage	Dissimilarity	Human Opportunity Index	Coverage	Dissimilarity	Human Opportunity Index
National	24.1	25.4	18.0	37.1	23.4	28.4
Urban	45.6	24.0	34.7	62.4	19.0	50.6
Rural	20.7	23.3	15.8	33.9	23.0	26.1
Tigray	60.2	8.7	55.0	68.6	8.1	63.0
Afar	7.3	49.5	3.7	11.4	50.2	5.7
Amhara	26.2	13.7	22.7	41.5	20.1	33.2
Oromia	15.4	28.9	11.0	23.2	22.9	17.8
Somali	11.1	42.9	6.3	18.1	28.4	13.0
Benishangul	26.5	17.8	21.7	64.8	12.7	56.6
SNNPR	24.0	18.8	19.5	49.2	11.3	43.6
Gambela	18.1	33.5	12.1	38.4	25.1	28.8
Harari	41.2	21.9	32.2	38.4	25.1	28.8
Addis Ababa	75.6	8.6	69.1	91.3	2.1	89.4
Dire Dawa	56.2	11.4	49.8	69.8	13.1	60.6

Source: Own calculation based on DHS 2011 and 2016

As stated above, the Shapley Decomposition estimates the marginal contributions of the various predictors to immunization opportunity inequality. The findings from the Shapley decomposition are shown in Tables 3.6 (national, urban, and rural) and 3.7 (by region). In both periods, our study indicates that household-specific characteristics and regional disparities are the most important contributors to immunization inequality. At the national level, in 2011, regional variations (32.01%), distance to the nearest health center (14.16%), household socioeconomic status (11.71%), and mother's religion (10.02%) are important contributors and together account for 68 percent of the variation in the dissimilarity index. In 2016, regional variations (28.7%), mother's religion (16.12%), place of delivery (12.94%), and maternal education (10.79%) contribute about 69 percent to national immunization inequality. Although the role of regional differences declines by 3.27 percent over the two periods, the regions are far from becoming homogeneous in terms of their immunization outcomes. Overtime, the Ministry of Health has been trying to increase access to facilities for the delivery of children and thus this circumstance's role in explaining immunization inequality has increased recently. For the rural group of children, the distance to the nearest health center as a problem contributes to explaining 9.6 percent of the inequality index in 2011. This value marginally increases to 10.04 % in 2016. For their urban counterparts, the role of distance to the nearest health center in explaining immunization inequality declines significantly from 10.34 percent to 0.76 percent.

For a given year, we note differences in the contributions of the various circumstances among rural and urban areas. In 2011, place of delivery was responsible for 7.13 % of the changes in the dissimilarity index in urban areas. In the rural areas in 2011, place of delivery was contributing to only 1.65 % towards the dissimilarity index. This is because in the rural areas the predominant type of delivery for majority of the mothers was at home through the support of traditional birth attendants. Overtime with increased government efforts to increase health facilities particularly in rural areas, the role of place of delivery in affecting immunization status has become more pronounced. In the year 2016, the contribution of place of delivery to the dissimilarity index has increased to 10.85 %.

Table 3. 7 Shapley decomposition of the D-Index (By National, Urban and Rural)

	2011			2016		
	National	Urban	Rural	National	Urban	Rural
Place of Residence	8.80			4.34		
Gender	1.10	3.41	0.35	0.07	1.31	0.09
Mother's age	2.28	0.71	4.52	0.62	1.85	0.53
Place of delivery	6.45	7.13	1.65	12.94	11.32	10.85
Mother's religion	10.02	2.76	19.93	16.12	4.65	21.92
Employment status	0.31	1.54	1.92	4.30	0.74	4.83
Media access	4.96	11.53	1.46	2.65	11.35	0.65
Distance problem	14.16	10.34	9.60	9.74	0.76	10.04
Education level	8.20	16.29	4.27	10.79	24.57	8.14
Economic status	11.71	4.61	6.72	9.69	6.50	7.79
Region	32.01	41.68	49.58	28.74	36.94	35.17

Source: Own calculation based on DHS 2011 and 2016

Media access does not seem to influence immunization status of rural children. In both 2011 and 2016 media access contributes to close to 12% of the disparity in immunization among urban households. Attributed to the proliferation of increased road networks, the importance of distance to health facilities as a factor explaining variations in childhood immunization has declined for urban Ethiopia over the study period. Long distances and inaccessible health facilities for most of the rural population impacts immunization inequality in both 2011 and 2016. The role of maternal education in explaining immunization inequality increases across both periods in both rural and urban Ethiopia. The role of gender in explaining immunization inequality is minimal in both periods.

The Shapley decomposition by regions in Table 3.7 highlights the main contributors to immunization gaps for each region. The economic status of the household is an important driver of immunization inequality across many regions but mainly in Tigray, Afar, Oromia and Amhara. Surprisingly in Addis Ababa alone media access contributes 30% to immunization inequality. This may be due to recent findings in the literature which suggest the existence of substantial inequities to immunization coverage in urban settings, with large, underserved populations in slum and informal settings. The place of delivery is the most important contributor to inequality for the city of Dire Dawa and the region of Somali in 2016.

Table 3. 8 Shapley decomposition of immunization by region

Region	Year	Place of residence	Gender	Mother's age	Place of delivery	Mother's religion	Employment status	Media access	Distance is a problem	Education level	Economic status
Tigray	2011	9.7	14.4	13.2	5.7	14.1	12.2	4.0	3.0	6.7	17.1
	2016	13.0	1.3	0.3	7.2	7.7	3.3	1.1	10.6	19.3	36.3
Afar	2011	23.3	0.2	5.4	4.6	1.5	6.1	5.5	13.7	16.9	22.7
	2016	13.6	7.2	2.2	15.0	10.2	4.3	1.2	6.6	13.9	25.8
Amhara	2011	16.8	3.1	17.6	0.9	10.7	14.3	2.3	3.6	5.6	25.2
	2016	6.2	1.6	2.6	7.9	3.9	0.7	1.9	19.6	22.9	32.8
Oromia	2011	16.0	3.7	3.5	6.9	15.0	1.7	7.1	17.7	16.1	12.3
	2016	3.7	1.2	4.6	11.4	14.2	15.6	4.2	5.8	14.6	24.6
Somali	2011	5.0	0.1	0.2	3.0	7.9	2.4	2.7	18.3	10.4	50.0
	2016	6.2	0.6	0.5	37.5	0.6	4.1	0.4	33.1	2.0	15.1
Beninshangul	2011	8.5	6.5	0.4	1.9	16.3	1.1	5.3	8.1	19.1	32.7
	2016	2.7	6.9	1.4	17.5	18.9	22.2	0.4	7.5	13.0	9.6
SNNPR	2011	13.1	1.4	2.5	6.5	0.7	0.5	10.6	28.4	14.4	21.9
	2016	2.7	15.6	1.9	26.3	7.5	2.8	2.8	2.8	29.3	8.3
Gambella	2011	6.3	20.7	19.7	15.1	0.7	3.6	2.7	13.9	6.7	10.6
	2016	10.1	3.2	3.4	20.8	5.8	2.9	4.8	5.9	24.3	18.7
Harari	2011	25.7	4.6	1.9	17.7	4.3	2.0	3.0	25.8	10.6	4.4
	2016	10.1	3.2	3.4	20.8	5.8	2.9	4.8	5.9	24.3	18.7
Addis Ababa	2011	0.0	4.4	9.2	31.9	3.7	3.4	1.1	3.3	39.5	3.5
	2016	0.0	2.2	3.6	9.5	1.7	13.9	29.9	12.3	12.0	14.9
Dire Dawa	2011	7.5	2.7	1.2	9.3	44.8	3.7	7.6	4.6	11.9	6.8
	2016	15.2	5.2	0.7	47.2	10.0	1.4	1.7	2.0	7.5	9.0

3.6. Conclusion

Common vaccine-preventable diseases, including measles, diarrhoea, pneumonia, that are responsible for causing two to three million childhood deaths worldwide annually, could be averted through the use of vaccines as a safe and effective public health intervention. To achieve the Sustainable Development Goals (SDG) targets of under-five mortality of no more than 25 per 1000 live births, the prevention of major childhood illness via immunization is critical. These targets require renewed efforts in expanding coverage and ensuring timeliness of immunization. But a successful immunization system is one that delivers vaccines with high equity across social and ethnic strata, parental education, and geographies. Unfortunately, in countries like Ethiopia, the chance of getting vaccinated is largely dictated by circumstances outside the children's control. The circumstances are defined along the lines of the child's birthplace, parental education and wealth, location of residence and other factors. The findings in our study confirm immunization in Ethiopia increasingly suggest the presence of a social gradient in favor of certain social groups.

The study examines equality of opportunity in the sample of Ethiopian households to understand the determinants of child vaccination status in Ethiopia and to measure coverage and inequality. The study also explores how predisposing circumstances like sex of the child, household characteristics, distance to the health facility and regional variations contribute to inequality of opportunity in immunization. We use the most recent two rounds of the Ethiopian Demographic and Health Survey, which were conducted in 2011 and 2016.

According to our findings, the HOI for full immunization has increased in both rural and urban areas but largely attributed to gains in coverage. The important predictors of complete immunization are delivery in a health facility, maternal primary education, mother practicing Christianity, and whether distance to the nearest health facility is considered as problem. This is particular the case for the rural segment of children. The dissimilarity index for Ethiopia only marginally decreased from 25.4 percent to 23.4 percent. Both the HOI and dissimilarity indices have wide regional variations.

Our decomposition analysis confirms that predisposing factors such as birthplace, gender, parental education, wealth, and other socioeconomic factors that are largely beyond the control of children have a significant influence both on immunization status and the inequality of opportunity. Findings from the Shapley decomposition reveal that regional variations, distance to health facilities, religion affiliations, household economic status, and maternal education consistently contribute to the

inequality. Although the role of regional differences has declined by 3.27 percent over the two periods, the regions are far from becoming homogeneous in terms of their immunization outcomes. Most of the hot spot areas in terms of poor immunization outcomes cluster in the regions of Afar, Somali and Gambela. These areas are characterised by nomadic pastoralists and other mobile groups such as migratory workers often beyond the reach of established health care programs. A strategy specific to migrant populations such as forging relationships with traditional leaders and initiatives to integrate human and animal vaccination campaigns may prove useful in accommodating such sections of society. Some of these regional disparities in inequality of opportunity may be attributed to uneven increases in growth and uneven spending on the government led health programs. The findings also call for substantial policy revisions if the goal of universal access to full immunization.

Addressing gaps in vaccination coverage in Ethiopia will necessitate a major focus on raising mothers' educational levels, particularly by paying attention to the discrepancies in educational attainment between geopolitical zones and socioeconomic differences such as religion. Access to a health facility is a significant barrier to vaccine take-up and determinant of immunization completion. Policy interventions can be to improve the road infrastructure to ease the transportation burden. New initiatives such as incentives for showing up at health centers[43] can be put in place to improve the demand for childhood immunization among caregivers.

This paper singles out the factors that lead to the inequality of opportunity in immunization. Government policies should therefore focus on reducing these factors and access patterns to change immunization inequality over time. At the same time, however, monitoring the effectiveness of such policies on a regular basis can reveal whether programs and policies are on track to meet their objectives. This paper is a contribution in that direction, providing insights to achieve universal child immunization coverage in Ethiopia. To sustain gains in immunization opportunities, policies aimed at reducing inequality at regional levels and improving coverage must be combined. The findings on relative contributions are especially important because they enable policymakers to take appropriate measures and focus on the major contributors to reducing inequality of opportunity

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[43] See - Selecting the Most Effective Nudge: Evidence from a Large-Scale Experiment on Immunization https://www.nber.org/papers/w28726

Appendix 3

Table *A.3.1:* Logit - marginal effects

VARIABLES	2011			2016		
	(1) National	(2) Urban	(3) Rural	(4) National	(5) Urban	(6) Rural
Female	0.007	0.158	-0.005	-0.014	0.047	-0.020
	(0.699)	(0.372)	(0.811)	(0.535)	(0.382)	(0.396)
Health facility	0.034	0.326	0.045	0.091***	0.144	0.092***
	(0.421)	(0.117)	(0.397)	(0.004)	(0.110)	(0.006)
Mother age	0.003**	0.011	0.003**	-0.000	-0.004	-0.000
	(0.013)	(0.522)	(0.025)	(0.828)	(0.334)	(0.859)
Employed	-0.008	0.053	-0.008	0.048	-0.035	0.063*
	(0.703)	(0.772)	(0.727)	(0.101)	(0.462)	(0.052)
Primary education	0.051**	0.563**	0.037	0.085***	0.325***	0.070***
	(0.043)	(0.011)	(0.169)	(0.001)	(0.000)	(0.007)
Secondary education	0.051	0.474	0.088	0.107	0.219**	0.139*
	(0.522)	(0.136)	(0.539)	(0.131)	(0.029)	(0.099)
Teritery education	0.027	0.095	-0.006	0.147	0.364***	-0.136
	(0.671)	(0.796)	(0.948)	(0.113)	(0.000)	(0.154)
Christian	0.041	0.558**	0.039	0.096**	0.039	0.096**
	(0.166)	(0.010)	(0.231)	(0.014)	(0.678)	(0.023)
Middle income	0.015	-1.330	0.016	0.049	0.031	0.048
	(0.528)	(0.384)	(0.485)	(0.153)	(0.889)	(0.177)
Rich	0.061**	0.595	0.063**	0.087***	-0.001	0.084**
	(0.038)	(0.256)	(0.034)	(0.010)	(0.997)	(0.017)
Media access	0.117**	0.275	0.064	0.123	0.099	0.077
	(0.037)	(0.274)	(0.397)	(0.189)	(0.345)	(0.463)
Distance problem	-0.072***	-0.538***	-0.046	-0.051*	-0.006	-0.057*
	(0.008)	(0.004)	(0.126)	(0.070)	(0.946)	(0.054)
Urban	0.044			-0.071		
	(0.304)			(0.141)		
Observations	3,703	692	3,011	3,604	726	2,878
Regional dummy	YES	YES	YES	YES	YES	YES
standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1						

Notes: Regional dummies included with Tigray as the reference category.

Source: Estimation based on DHS 2011 and 2016.

Table A.3.2 Coverage, Dissimilarity, HOI in 2011: partial immunization vs non-immunization & non-immunization vs full immunization

	Coverage	Dissimilarity	HOI
Non-immunization and Partially Immunization			
National	80.43	5.28	76.18
Urban	85.17	8.79	77.69
Rural	79.91	5.58	75.45
Non-immunization and Full Immunization			
National	61.90	19.40	49.89
Urban	84.99	12.37	74.48
Rural	56.45	21.71	44.19

Table A.3.3: Shapley decomposition of the D-Index in 2011: partial immunization vs non-immunization & non-immunization vs full immunization

	Non-immunization and Partial Immunization			Non-immunization and Full Immunization		
	National	Urban	Rural	National	Urban	Rural
Place of Residence	1.68			6.22		
Gender	0.71	0.16	5.51	1.05	4.39	0.28
Mother's age	0.74	2.21	5.24	1.79	2.66	3.80
Place of delivery	3.93	1.86	6.34	6.08	7.87	2.17
Mother's religion	7.36	7.81	3.73	8.92	3.03	14.15
Employment status	1.01	1.51	0.44	0.62	0.66	1.99
Media access	0.51	0.92	6.80	3.25	9.10	0.55
Distance problem	10.69	9.29	2.19	13.05	5.48	9.89
Education level	21.66	18.44	27.02	13.26	23.80	9.63
Economic status	1.65	0.55	1.53	6.97	3.06	3.49
Region	50.05	57.23	41.20	38.79	39.96	54.04

Table A.3.4: Coverage, Dissimilarity, HOI in 2016: Partial immunization vs non-immunization & non-immunization vs full immunization

	Coverage	Dissimilarity	HOI
Non-immunization and Partially Immunization			
National	72.08	6.31	67.53
Urban	90.80	6.34	85.04
Rural	70.73	6.21	66.34
Non-immunization and Full Immunization			
National	67.85	15.66	57.23
Urban	94.75	3.60	91.34
Rural	63.66	16.37	53.24

Table A.3.5: Coverage, Dissimilarity, HOI in 2011: Partial immunization vs non-immunization & non-immunization vs full immunization

	Non-immunization and Partial Immunization			Non-immunization and Full Immunization		
	National	Urban	Rural	National	Urban	Rural
Place of Residence	7.37			5.21		
Gender	0.51	14.68	0.03	0.23	8.79	0.12
Mother's age	0.67	3.80	0.57	0.30	1.67	0.29
Place of delivery	4.89	0.72	3.11	11.43	5.58	9.57
Mother's religion	12.12	3.10	14.32	16.47	4.95	21.14
Employment status	3.07	12.11	1.87	4.54	8.07	4.50
Media access	3.35	1.19	3.90	3.18	5.27	2.18
Distance problem	10.05	10.55	7.57	11.00	5.07	10.01
Education level	9.65	21.64	13.11	10.60	25.55	10.09
Economic status	25.44	2.91	28.57	12.09	3.14	11.82
Region	22.88	29.31	26.94	24.96	31.92	30.29

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