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Gendered barriers to formal healthcare utilization: Modelling healthcare demand in a low-resource setting

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Gendered barriers to formal healthcare utilization: Modelling healthcare demand in a low-resource setting

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Abstract

This paper develops a model of healthcare demand to study healthcare choices in resource-limited settings with poor health indicators, especially for women. Using data from rural Nigeria on individual illnesses and injuries as well as the entire portfolio of locally available providers, we estimate the effect of price, distance and quality on access to care, focussing on the heterogeneous responses to these three factors by gender. We find that women are more price sensitive than men, in particular in households where they have low bargaining power, while being equally responsive to quality or distance. Using our model to simulate ex-ante the impacts of price interventions, we predict that a full price subsidy in public clinics would substantially increase both men's and women's access to formal care, and almost eliminate the observed gender gap in formal healthcare utilization. Subsidizing both public and private clinics only marginally improves overall access, but it fully eliminates the observed gender gap in addition to broadening the capacity of the health sector to respond to increased demand when public facilities have limited capacity.

Keywords: Universal health coverage, healthcare provider choice, gender heterogeneity, intra-household bargaining, price endogeneity

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1 Introduction

With more than half the world's population lacking access to essential healthcare (WHO, 2017), there is still a long road ahead before reaching universal health coverage. Women in particular bear a disproportionate share of the global burden of disease, despite political commitments reflected in Sustainable Development Goal 5 to achieve gender equality in health (Weber *et al.*, 2019). Yet, quantifying the extent of gender inequities in access to healthcare is challenging for a number of reasons: differences in sex (biological factors) and gender are intertwined, most notably with respect to sexual, reproductive and maternal health; sex and gender may interact with behavioral factors such as risk attitudes and social preferences; and gender inequalities in health may be context-specific, due to diverse cultural norms and health systems. Survey-based data to shed light on these mechanisms are limited, particularly in low-resource settings.

Addressing the sources of gender inequalities in healthcare access requires an in-depth understanding of how people decide whether and where to seek care. In many developing countries, dismal conditions of health facilities are common, which prevent people from seeking formal care when needed (e.g. Banerjee *et al.*, 2004; Chaudhury *et al.*, 2006; Das *et al.*, 2008). Because of a concentration of (better quality) clinics and hospitals in urban settings, adequate healthcare is particularly difficult to find in rural and remote areas. Moreover, health financing systems – especially in the African context – are often predominantly based on out-of-pocket payments instead of pre-payment and risk-pooling (WHO, 2020). This hits the poor particularly hard. As a result, people may delay seeking care when needed, seek cheaper care of lesser quality, forego care all together, or instead spend large sums out-of-pocket for treatment, resorting to harmful strategies such as selling livestock, taking children out of school or reducing food intake to cover these costs. Estimates suggest that about 800 million people spend more than 10 percent of their household budget on healthcare, and almost 100 million people fall into extreme poverty each year due to ill health (WHO, 2017).

Whereas these circumstances affect both male and female health, women are often at a greater disadvantage. An expanding literature discusses the complex gendered pathways to health resulting in health inequities in many countries (Heise *et al.*, 2019). These mechanisms are more pronounced in areas where women suffer from structural disadvantage and discrimination. In many countries throughout the world, men are the dominant decision-makers in the household. Women have less resources, information and personal autonomy than men, and are often dependent on their husbands' approval for traveling, utilizing healthcare, or payment of medical services (Grown *et al.*, 2005;

Filippi *et al.*, 2006; Roy & Chaudhuri, 2008). Not surprisingly, women's empowerment status is a strong predictor of access to the most basic maternal, and sexual and reproductive health services (Ahmed *et al.*, 2010). Indeed, women –and in particular African women, continue to suffer from limited access to affordable and good quality healthcare, despite the steady improvements in health statistics for the African region over the past decades (WHO, 2014).

This article aims to advance our knowledge on how to reduce the gender bias in health-care access in low-resource settings. With a structural model we study how quality, affordability and (geographic) accessibility of healthcare services differentially affect health-seeking decisions of men versus women, and we predict the effectiveness of specific price interventions in enhancing access to formal healthcare by gender.

Identifying the determinants of healthcare choices has been an active research topic in the past decades. Traditionally, provider choice models have been estimated for this purpose, highlighting three main groups of factors: direct costs, indirect costs and quality of care. Direct costs, such as fees for treatment, are an important impediment to accessing healthcare services, especially for the poor. Indirect costs, such as distance, transportation costs, or the opportunity cost of foregone income, are also crucial determinants of the demand for healthcare. These indirect costs can be major rationing devises in remote areas and resource-constrained settings (Dor *et al.*, 1987; Borah, 2006; Sarma, 2009; Adedini *et al.*, 2014). The third key factor is quality of care. Several studies highlight the implications of quality of services on health provider choice (Haddad & Fourier, 1995; Akin & Hutchinson, 1999; Sahn *et al.*, 2003; Klemick *et al.*, 2009). In these studies, the phenomenon of bypassing low quality facilities in search of superior care is a recurrent finding.

In line with this literature, we use a rich household survey collected in 2009 among about 6,000 individuals in rural Kwara State, Nigeria.[1] The survey gives detailed information on demographic and socio-economic characteristics, health status, healthcare utilization and health expenditures by type of illness. It contains GPS coordinates for each household dwelling and a full census of health facilities in the area, from which a matrix of distances can be calculated. These data are combined with information on the quality of health facilities from medical technical quality assessments.

We specify a structural model of demand for care and allow individual preferences to depend on unobservable characteristics that may be correlated across different alternatives, using a multinomial choice model with random parameters (mixed logit),

[1] The survey was collected by the Amsterdam Institute for Global Health and Development (AIGHD) and the University of Ilorin Teaching Hospital (UITH) to serve as a baseline for the evaluation of a health insurance program implemented by the PharmAccess Foundation, the Health Insurance Fund and Hygeia Ltd.

hence leaving flexible substitution patterns. Importantly, we use a control function to instrument for endogenous price setting. In most of the literature, prices paid at various providers are treated as exogenous.[2] This may not be appropriate, for example when hospitals with higher quality and a better reputation charge higher prices, and quality is not perfectly observable. To allow for a direct comparison of male and female responsiveness to price, quality and distance, we investigate access to care for *acute illnesses and injuries* instead of women-specific outcomes such as sexual and reproductive health.

Our general findings confirm existing evidence: The higher the price or the longer the distance to a particular provider, the less likely it is that a patient will choose this alternative; at a given price and distance, better quality increases demand. We show that instrumenting for endogenous prices substantially alters the findings. Assuming prices exogeneity instead would have led to substantially overestimating the price effects on healthcare demand, which, with commonly used multinomial conditional logit models, may even yield positive price elasticities.

The gender analyses show that women are significantly more price sensitive than men at every level of income, especially for prices in the formal sector, while being equally responsive to quality or distance. This might explain their lower access to the better-quality but more expensive formal care. In our analysis, we explore various potential explanations for the greater price sensitivity of women, including differences in illness types, gender discrimination on the part of providers, differential sensitivity to travel distance, and intra-household bargaining position. Our findings suggest that low female empowerment is a key driver of gender heterogeneity in price responses. Women with low bargaining power, as proxied either by spousal age differences or spousal differences in weekly income, are substantially less likely to utilize both public *and* private formal care when prices increase compared to the men in their households. Still, limited decision-making power does not provide a full explanation of the observed gender differences, as women with high bargaining power remain less likely than their husbands to visit private clinics when costs increase. Our predictions suggest that a full price subsidy in public clinics would substantially reduce the observed gender gap in formal healthcare utilization, increasing female utilization of public and private clinics by 50 percent. This result is driven by the greater female price responsiveness. Subsidizing access to both private and public clinics only marginally improves overall access to formal care, but fully eliminates the gender gap. In addition, such a comprehensive policy

[2] This is appropriate in contexts where prices for treatment are fixed by the central government, as it is, for example, in applications of provider choices among NHS hospitals (Beckert *et al.*, 2012), or in samples of patients fully insured (Varkevisser & van der Geest, 2007).

offers more opportunities to respond to the increased demand when public facilities have limited capacity.

Our paper thereby contributes to two strands of literature. First, we investigate heterogeneity in the main determinants of healthcare utilization to understand why women persistently lag behind men in access to care, in spite of active health policies. Specifically, we estimate self- and cross-price (and quality and distance) elasticities—not only along income levels, as has been widely investigated before (Dor *et al.*, 1987; Sarma, 2009; Deaton, 2013), but also for men versus women. To our knowledge, such a systematic gender-specific modelling of price, quality and distance responsiveness does not yet exist in health provider choice studies. One possible explanation is that estimating structural models of healthcare choices requires rich data sets on both patients and providers, which are mostly unavailable in resource-constrained settings. Studies in high-income countries have not shown systematic evidence of a pro-male gender gap in healthcare utilization: in fact women tend to use more healthcare services than men (see for example Bertakis *et al.* (2000); Ladwig *et al.* (2000); Heise *et al.* (2019); Shalev *et al.* (2005)), a result largely explained by differential need factors based on maternal health, sex- and age-specific conditions, chronic diseases, and health-related quality of life (Redondo-Sendino *et al.*, 2006; Mustard *et al.*, 1998). In contrast, this paper explores gendered pathways to healthcare utilization in a resource-limited setting, where gender inequalities are more likely to occur due to poor health insurance coverage, poor health systems, and limited household resources. By doing so, we directly contribute to the literature studying the roots of gender inequalities (for a review see Jayachandran (2015)).

Second, we contribute more generally to the literature on structural modelling of healthcare choices by using the strengths of our rich data on individuals falling ill and the entire portfolio of locally available providers. Specifically, our dataset allows us to examine the relative importance of the three main factors (price, distance and quality) simultaneously. Empirical analyses so far often suffer from several drawbacks. Due to data limitations, most studies focus on a subset of the main determinants, rather than on price, quality and distance simultaneously. For example, Bolduc *et al.* (1996), Borah (2006) and Sarma (2009) include direct and some form of indirect costs, such as distance, but do not have information on quality; Klemick *et al.* (2009) analyse quality and distance but do not have information on treatment costs; and Akin *et al.* (1995) use information on both prices and quality but not on distance. In addition, existing studies generally use limited datasets that include information on the chosen providers but not on the unchosen alternatives. In contrast, we are able to take into account the location and characteristics of *every* single health provider that is operating in the study area. The inclusion of information on the entire portfolio of available health services is essential to understand patterns of substitution induced by changes in costs and quality, including the option of informal care and self-treatment. We also allow prices to be endogenous, which turns out to be crucial.

The outline of the paper is as follows: Section 2 describes the context, the survey population, and the survey instruments. Section 3 describes the structural model of provider choices and the identification strategy. Section 4 presents our results from alternative models, and assesses differential sensitivity of male and female health provider choices to changes in price, distance and quality by computing own- and cross-elasticities separately for men versus women. Section 5 discusses the policy implications of price interventions in the public and the private sector, while Section 6 concludes.

2 Data

2.1 Context

The analysis is based on a representative household survey (based on a stratified, clustered, self-weighted random sample) that was carried out in 2009 among 1,450 households in Kwara State, Nigeria (Van der Gaag *et al.*, 2010). Nigerian health indicators are among the worst in the world, with a life expectancy at birth of 55.2 years compared to 61.2 for the African region and 72.0 world-wide. Maternal mortality rate is almost highest in the world at 917 per 100,000 live births, compared to African and global rates of 525 and 211, respectively. The under-5 mortality rate is 120 per 1000 live births, compared to 76 in the African Region and 39 globally (WHO, 2020). Healthcare access and utilization are unequal (Titus *et al.*, 2015), which is partly explained by socio-cultural factors (Azuh *et al.*, 2015). As in other countries, empowerment and decision-making autonomy of Nigerian women play a crucial role in health outcomes and access to care (Antai, 2011, 2012; Singh *et al.*, 2012; Adedini *et al.*, 2014; Ariyo *et al.*, 2017; Soetan & Obiyan, 2019).

Kwara is a predominantly rural state in the North-Central of Nigeria with an estimated poverty rate of 62 percent around the time of the survey, slightly above the national average, although the poverty headcount rate has dropped dramatically in the past decade to 20 percent (NBS, 2012, 2020). Healthcare financing and delivery in Kwara is based on a mixed system of public and private care with low quality of services (Gustafsson-Wright *et al.*, 2017). Less than 2% of the study population was enrolled in health insurance at the time of the survey.

The main ethnicity in Kwara is Yoruba, the second-largest ethnic group of Nigeria. Yoruba women are relatively autonomous in generating their own income, free to come and go in daily life, and they enjoy greater intra-household decision-making authority compared to women of other ethnic groups such as the Hausa and Igbo (Kritz & Makinwa-Adebusoye, 1999). Nevertheless, social norms dictate a largely subordinate role for wives to their husbands, especially in traditional rural areas (Zeitlin *et al.*, 1995).

Seniority among the Yoruba is partly determined by age. Husbands generally have a final say in health-related decisions regardless of their age. Wives gain decision-making power as they grow older (Soetan & Obiyan, 2019), but the proportion of women who can decide on health remains well below the proportion of men at all ages (Angel-Urdinola & Wodon, 2010). Spousal age differences have a significant negative effect on wives' decision-making power even after controlling for individual-level characteristics such as education, employment, and income-generation (Kritz & Makinwa-Adebusoye, 1999). Differences in relative income are another key determinant of women's intra-household bargaining power with respect to household resource allocation and health (Ariyo *et al.*, 2017; Soetan & Obiyan, 2019; Opata *et al.*, 2020).[3]

2.2 Sampling methodology

The survey data include detailed information on health events, healthcare utilisation and health expenditures as well as demographic and socio-economic characteristics of all 5,989 household members. In the sample, 1,732 individuals reported having suffered from an acute illnesses or injury in the 12 months preceding the survey, 346 from a chronic disease, and 761 visited a healthcare provider for reasons other than illness, such as family planning, pregnancy or preventive care.

Since healthcare utilisation is likely to differ across health problems and we need a large sample to estimate multinomial discrete choice models, our analysis focuses on the healthcare utilization of the 1,732 individuals who reported suffering from acute illnesses and injuries. Acute illnesses and injuries are also more likely to be unanticipated events, as opposed to chronic ailments or problems linked to reproductive health. Chronic conditions and pregnancy may induce patients to (temporarily) migrate closer to the facility where they (expect to) receive treatment. For acute healthcare utilization on

[3]Polygyny is another factor that might affect women's bargaining power and health outcomes (Bove & Valeggia, 2009; Barr *et al.*, 2019). This is however a minor concern in our context, since less than 3% of the households in our study sample are polygynous.

the other hand, patient's location of residence is more likely to be exogenous.

A comparison of the full sample with our patient sample shows that there are no significant differences between the two other than age (see Appendix Table A.1). Individuals who reported acute illnesses or injuries are older on average than the general population at 31.2 and 26.4 years, respectively, which is not too surprising given that health deteriorates as people grow older. Along other dimensions, individuals in both samples are very similar. They are living in equally poor households, with mean aggregate household consumption just above 400,000 Naira per annum (approx. 2,680 USD)[4] in both samples.[5] At an average household size of 5.3 members, this comes down to less than 2 USD per person per day. There is also a good balance across the samples along other dimensions which could be linked to a disadvantaged position, such as gender and years of schooling. The percentage of women is equal in both samples at 51 percent, as is the average years of completed schooling by adults (3.7 for adult women and 6.1 for adult men). The average spousal age gap, a proxy for intra-household bargaining power calculated as the difference between the ages of the household head and his spouse, is similar across the two samples at an average of 10 years. On average, 70% and 75% of individuals in the full and patient sample, respectively, live in a family with an above-median age differential between the spouses.[6] Similarly, spousal differences in weekly income do not differ significantly between the full and the patient samples at 2,513 and 2,080 Naira (16.8 and 13.9 USD), respectively.

Restricting our analysis to ill persons will however introduce a selection bias if the individuals *least* likely to seek care are also less likely to be included in the patient sample. This could be the case for instance if they are more likely to die. Conversely, selection bias may also arise if those *more* likely to seek care would migrate for health reasons and drop out of the sample as a result. Such biases affect the representativeness of our sample and may limit the conclusions that can be drawn from the model for the overall population of acutely ill or injured people. To investigate this, we investigate attrition from the full sample. Although we do not have information in our 2009 dataset on individuals who died or who left the households in the year prior to the survey, we can use the migration roster of a follow-up survey held in 2011 among the same households to investigate the size of subsequent attrition and its causes. Assuming that attrition patterns are similar across years, this will give us a sense of selection in the 2009 dataset as well.

[4]The exchange rate in June 2009 was 0.67 USD for 100 NAIRA.

[5]This is calculated as the aggregate of weekly imputed food expenditures (including gifts and own harvest), and monthly and annual non-food expenditures for the full household.

[6]These percentages are calculated on the number of individuals for which we have age information for both spouses.

Two years after the baseline, attrition due to death is low: 93 individuals died, or 1.6% of all individuals in our baseline sample. The remainder of attritors migrated mostly for reasons of employment, education, marriage, to follow family or to care for relatives; only 8 individuals (0.1% of the baseline sample) left their households since baseline in search of healthcare. Zooming in on the deceased, the 2011 survey includes details on 53 individuals who had died in the sampled households: 64% of them were male; the mean age at death was 41 years old with about one-third of deceases before age ten and one-third after age 65. Causes were various but mostly acute, ranging from malaria and pneumonia to a snake bite or an accident, with a few cases of cancer and old age. Whereas 77% of the individuals had needed healthcare at the time of their death, only 8% of those in need (i.e. 3 individuals) were reported to have had insufficient financial means to pay for medical treatment or transportation to the health center. In view of the low numbers of health-related attrition *after* the 2009 survey, we have no reason to suspect that the 2009 patient sample itself is substantially biased towards those least or instead most likely to seek care.

As is common in household surveys with recall periods, we cannot fully rule out underreporting of e.g. foregone care for minor illnesses (Das *et al.*, 2012). As such, our dataset may capture relatively more serious illnesses and injuries for which formal care was sought (Nelissen *et al.*, 2020).

A census of health facilities in the study area identified all public and private clinics, health posts, maternal and child health centers, and other formal facilities. We merge the information from the household survey with the technical quality assessments of the 21 main health facilities available in the study area, as well as the GPS coordinates of households and health facilities.[7] The following subsection explains the construction of the key variables in our analysis —provider type, price, quality and distance.

2.3 Survey instruments

Provider types — When investigating the effect of prices, quality and distance on health-seeking behaviour, it is important to include the (outside) option of informal and/or self-care to allow for the choice of exiting the formal market.[8] In our analysis we group all informal (non-qualified) and self-care options under the header of informal care, which is chosen in 31% of the cases. This includes no treatment or self care

[7] The analysis excludes facilities that were visited in less than 0.5 percent of health events and focuses on the remaining 21 facilities out of the 72 identified by the census. Quality data for these 21 facilities were collected retrospectively in 2011 except for two clinics that were assessed at the time of the survey.

[8] For a more qualitative description on informal and formal health provider choices in Nigeria and Kwara state in particular, see Olasehinde (2018); Nelissen *et al.* (2020)

(23%), patent medicine vendors (70%), alternative medicine vendors (2.8%), traditional and spiritual healers (3.7%) and paramedics (0.5%). Alternatively, patients may opt for one of the 21 health facilities, which include 8 private and 13 public clinics and health centers, as well for the option to see a private "doctor", which includes qualified doctors, nurses and midwifes with a private practice (90.8%) as well as medically trained pharmacists (9.2%).

Table 1 panel A shows patient characteristics by type of provider. Women are more likely than men to opt for informal or self-care – especially the least educated women. Men are more likely to visit public and to a lesser extent private facilities when ill, compared to women. Patients who choose informal care have lowest median aggregate consumption. When suffering from febrile illnesses, people are relatively more likely to go to informal providers. For most other symptoms, public facilities appear to be slightly preferred as the provider of choice, except for accidents and injuries in which case people are relatively more likely to visit a private clinic.

Imputed prices — In our dataset we observe the price each individual paid when visiting a particular provider. The average price per visit paid is 4,786 NAIRA (approx. USD 32) in the public sector and 2,965 NAIRA (approx. USD 20) in the private sector (Table 1 panel B). These prices represent about 1.5% and 0.9% of annual median household consumption, respectively. The observed mean price for formal care is between three and four times larger than the mean price of informal care and almost twice as much as the mean price for private doctors. However, these averages mask large differences; median price in public and private facilities is 2,366 and 2,586 NAIRA, respectively. The observed price for public healthcare utilization has a higher variance than prices paid at other types of providers, resulting in a relatively high mean (but not median) public price.

However, we also need a measure of the price that a patient would have paid at non-chosen providers. We impute the price an individual i would have paid had she visited provider j as the mean price actually paid by individuals attending provider j who were affected by the same illness as individual i. The type of illness is a major determinant of treatment costs. We identify five types (Table 1): febrile illnesses (such as malaria, typhoid fever or the flu; 54.0%), infections and pains (such as urinary tract or skin infections; 5.5%), respiratory diseases (such as pneumonia or coughing; 3.2%), accidents and injuries (burns, broken bones; 2.5%), and other (including the remaining illnesses, unclassifiable symptoms and missing information; 34.5%). Moreover, we would have liked to be able to classify illnesses into several levels of severity. Unfortunately we do not have such information in our survey.

In principle, we would like to group individuals on the basis of more characteristics, such as finer illness types, age groups and location of residence. However, since we use a large portfolio of 21 health facilities plus private doctors and informal care, observed prices become sparse as we account for finer grouping. For example, we may not observe a young women aged 20-30, living in location x and facing illness y for each provider. This would generate many missing values. Our strategy maintains the advantage of a large portfolio of providers while accounting for a classification of illnesses which is more disaggregated than what is usually done in the literature.

In a strict sense, the data do not reflect the price of a particular health service but the total costs per consultation, including diagnostic tests, treatments, and medicines – albeit disaggregated by illness type. Ideally, we would include precise measures of the price of specific services in the analysis. These are however not available, because patients often receive a bundle of treatments when visiting a provider, and they reported the total amount paid in the survey. Moreover, even if official price lists were available, this would not capture the high level of additional informal payments paid by patients in Nigerian clinics (Onwujekwe *et al.*, 2010). Hence, our analysis is based on costs proxied by expenditures, as it is standard in the provider choice literature. We note that transportation costs are not included in the price, as they are captured in the distance variable.

Table 1 panel B also shows the mean and median of imputed prices, which are in line with the mean and median observed prices, although they somewhat underestimates the prices paid in public facilities.

Distance — In addition to direct monetary costs, the distance to health providers may represent an important constraint to the use of health services. We measure distance using GPS coordinates of the household dwellings and the health facilities, and compute the great circle distance using the Haversine formula, which measures the shortest distance between two points along a path on the surface of a sphere.[9]

Since we do not have GPS coordinates of doctors, we use the average distance from the village to the nearest private doctor, qualified nurse or midwife as a proxy for distance to doctors.[10] For informal and self care, we assume that patients do not need

[9]The Haversine formula is: $d = 2rarcsin(\sqrt{sin^2(\frac{lat2-lat1}{2}) + cos(lat1) * cos(lat2) * sin^2(\frac{long2-long1}{2})})$ where $lat1, lat2$ and $long1, long2$ are latitude of point 1 and point 2 and longitude of point 1 and point 2, respectively; and r is the radius of the Earth, set to 6371.009 km and considered to be the Earth's mean radius by the International Union of Geodesy and Geophysics.

[10]Our survey provides community information about the traveling time and transport mode to reach the nearest tradition/spiritual healer, patent medicine vendor, alternative medicine vendor and private doctor, nurse, midwife. We converted this information into kilometric distances using the following velocity assumptions: 5km per hour by foot; 40 km per hour by public bus; 15 km per hour by bike.

to travel since most informal care is provided in or close to patients' dwellings, i.e. this distance is assumed to be equal to zero.

The nearest public (private) health facilities in our study region are located on average 21.5 km (16.4 km) from the households. Since only 12% of ill individuals have a car at their disposal, distance is likely to represent an important constraint to healthcare utilisation.

Provider quality — To proxy quality, we use three main indicators. First, we have detailed information on the number of qualified doctors operating in each facility within our portfolio. Second, we control for the number of beds, which is a proxy for capacity. Third, since power cuts are frequent in the area, we use functioning generator availability as a quality indicator, proxying for well-functioning amenities.[11] It correlates significantly with other indicators such as "How often does the facility have running water?" or "Does the facility have an operating theater?".[12] Private doctors are assumed to operate alone (i.e. to have one doctor) without bed or generator. Informal care is assumed to have no qualified doctor, no bed and no generator.

Private facilities are better equipped on average than public facilities: they employ more doctors, and 5 out of 8 private facilities have a functioning generator available at least most of the times in contrast to only 3 out of 13 public facilities. Nevertheless, more than one third of private clinics does not have a functioning generator, pointing to a bimodal distribution of quality within the private sector, with clinics both at the high and at the low end of quality. Public facilities are largest in capacity at an average of 32.5 beds compared to 8.8 beds in private facilities.

3 The econometric model

3.1 A model of health provider choice

An individual experiencing an acute illness faces the choice of seeking medical care at a health provider j within a set of alternative providers J.[13] In our case, the set of J choices is fixed and includes 23 alternative providers: the entire set of 21 health

[11] This variable is the response to the question "How often does the facility have a functioning generator?", coded as 1. No generator; 2. Sometimes; 3. Most of the times; 4. Always.

[12] It also correlates significantly with the number of major and minor surgical procedures carried out plus other clinical activities such as outpatient visits, curative cases, deliveries, number of immunizations, number of prescriptions, but these are mostly indicators of capacity; and positively (although not significantly) with road quality to the clinic and prevalence of power cuts.

[13] Only in 5.2% of the illnesses and injuries in our dataset, patients report two consults, the vast majority of them (90.4%) with both the first and the second consult at a formal clinic. In line with this observation, we treat the decision as a one-off choice, and we use the first reported provider in our analysis.

facilities available in the study area, a private doctor and the option of informal (or self-) care. The utility that person i obtains from alternative j is written as $U_{ij} = V_{ij}(x_{ij}, \beta_i) + \epsilon_{ij}$, where x_{ij} is a vector of observable variables including price, quality of care and provider's distance from the individual home; β_i represents the tastes of patient i and ϵ_{ij} is an unobserved random term that is distributed *iid* extreme value, independent of β_i and x_{ij}. Each patient chooses alternative j if and only if $U_{ij} > U_{il}$ for every $j \neq l$.

Within a standard conditional logit (CL) model, the *iid* assumption is restrictive in that it implies no correlation across alternatives (i.e. independence of irrelevant alternatives). Although this assumption is commonly adopted in the literature on health care provider choices because of ease of tractability of the CL, it is likely to be violated. Patients may not have the same substitution patterns when offered a choice of providers with the option of informal care, compared to without. For example, qualified local providers such as doctors may be closer substitutes to local informal drug vendors than to further-away health facilities. We relax this assumption by using a mixed logit model which allows the parameters associated with observable variables to vary randomly across patients.[14] β_i is unobserved for each patient i and varies in the population with density $f(\beta)$. This density can, for example, be specified normal with mean β and variance σ^2: these parameters can be estimated through maximum simulated likelihood. The variance in β_i induces correlation between alternatives in the stochastic portion of the utility.[15]

Heterogeneity in valuation of providers across patients is captured through the specification of the explanatory variables and/or the mixing distribution $f(\beta)$. In our specification, we allow some heterogeneity in valuations across individuals with different characteristics by interacting observable provider features with patients' demographic and socio-economic characteristics. An important source of heterogeneity highlighted in the literature is income heterogeneity in price elasticity of demand (Gertler et al, 1987). Therefore, we interact the price with a set of dummies for patient's income, proxied by aggregate household consumption. We also interact provider characteristics distance, price and quality with a dummy indicator for females in order to capture gender-related heterogeneity.

Finally, our specification of $V_{ij}(x_{ij}, \beta_i)$ allows x_{ij} to take flexible forms including quadratic and cubic terms. We discuss the final specification with the results in section 4, where we show the results from both the random parameter model and the con-

[14]In contrast, in a conditional logit specification the parameter β is assumed fixed.

[15]See Appendix A and Train (2001) for a detailed exposition on mixed logit estimation procedures.

ditional logit model for comparison. As patients may come from the same household and choices may be correlated within household, we cluster the standard errors at the household level. The coefficients' standard errors are estimated via bootstrapping with 500 replications.

3.2 Endogeneity of price

In a health provider choice model, concerns about the endogeneity of price arise naturally as the effect of price on demand is likely to capture the price effect plus the effect of unobserved factors correlated with it. Moreover, health care providers, in particular private and informal providers, may charge higher prices for patients who derive higher utility from their services, which would generate reverse causality.[16] We address the issue of endogeneity of prices by using a control function approach to estimate our model, which can be written as $U_{ij} = V_{ij}(p_{ij}, .) + \epsilon_{ij}$. Endogeneity concerns arise if price, p_{ij}, is correlated with the error term, ϵ_{ij}. The idea behind the control function correction is to derive a proxy variable that conditions on the part of p_{ij} which depends on ϵ_{ij}. If this can be done, the remaining variation in the endogenous variable will be independent of the error and hence standard estimation techniques will give consistent estimates.[17]

The implementation of the control function approach requires a set of exogenous instruments that influence the price paid to a healthcare provider but not directly the utility derived from the service. We use provider-specific instruments derived from the market conditions faced by each provider: the intuition is that competition by nearby providers affects the price charged by each provider and that competition is stronger between closer providers but that, after controlling for provider's quality, it does not affect the patient's utility other than through the price charged.

Since the set of available providers is very heterogeneous and our data do not include the same information for informal and formal providers, we need to adapt our instrumentation strategy by provider type. We instrument the price of the 21 public and private health facilities with a weighted measure of competitors' quality (measured by the number of qualified doctors available at competitors' facilities; competitors' avail-

[16]The quality measures we use are at the level of the provider, and, hence, are less likely to be endogenous in our model. We also assume that distances travelled to health providers are exogenous in the cases of acute illnesses and accidents that we study, differently from chronic illnesses.

[17]The problem of endogeneity of price is common in models of consumer choice where some product attributes are unobservable or poorly measured. Our approach is similar to e.g. Petrin & Train (2010) who analyse consumers' choice among television options. An alternative approach is the product-market control approach by Berry *et al.* (1995) and Berry *et al.* (2004). The latter has been widely applied (Crawford, 2000; Petrin, 2002; Nevo, 2001), but Petrin & Train (2010) note that the approach is not consistent in applications in which there are few observations per product, like in our case.

ability of generators and competitors' numbers of beds), where the weights are the inverse distances between health facilities. The rationale behind these instruments is that ceteris paribus, a fierce competition in quality by nearby facilities drives prices down.

We instrument the price of private doctors with the number of private medical staff (doctors, nurses and midwifes) operating in the village. The rationale is that harsh competition among qualified medical providers in the village lowers the price of treatment. Similarly, we instrument the price of informal care with the number of patent medicine vendors, traditional and spiritual healers and paramedics in the village. Furthermore we do not exclude that formal care providers such as clinics may compete with informal providers and doctors, which we capture by the average distance from the center of the village where the informal provider or doctor resides to the nearest clinic.

Hence, our instrumenting equation is written as:

$$\begin{aligned} p_{ij} \;\; = \;\; & \gamma_0 + \gamma_1 I(j = clinic) + \gamma_2 I(j = doctor) + \sum_{q=1}^{3} \gamma_q w q_j^q I(j = clinic) \qquad (1) \\ & + \gamma_3 g_j I(j = informal, doctor) + \gamma_4 N_j I(j = informal, doctor) + \delta' X_i + \epsilon_{ij} \end{aligned}$$

where p_{ij} is the price paid by individual i at provider j; $I(j = .)$ is an indicator function that equals one if provider j is a public or private clinic ($j = clinic$), a private doctor ($j = doctor$) or informal care ($j = informal$). $wq_j = \sum_l \frac{1}{g_{jl}} q_l$ is the quality of all j's competitor clinics l and weighted by factor w, the inverse of the geographical distance between provider j and provider l, (g_{jl}). We have three quality measures q, which we allow to enter non-linearly to maximize the model's fit. For private doctors and informal care, competition is proxied by the average distance from the center of their village of residence to the nearest clinic g_j, and the number of doctors or informal providers operating in the village, N_j. We constrain the parameter γ_4 to be the same for doctors and informal providers after hypothesis testing indicates the two parameters are not different. X_i is a set of individual characteristics that may affect the price paid by patients and includes gender, age, income quartiles, type of illness and its interaction with gender to capture potential gender heterogeneity in prices paid for different types of illnesses.

The main demand model is estimated in two steps. The first step regresses prices on the instruments and predicts the regression's residual. In the second step, the main demand model is estimated entering the residuals from the first step as additional control variable.

4 Empirical Results

This section presents the estimates of the determinants of healthcare demand in our setting. Our analysis focuses on understanding heterogeneity in health provider choices. The random parameter (or mixed logit) model (hereafter RPM) allows for individual heterogeneity in the effects of specific provider characteristics. Moreover, our chosen specification allows the vector of provider characteristics x_{ij} to enter the utility in a flexible form and to be interacted with individual characteristics. Specifically, it allows for the price effect to vary with individual income in line with the literature. We also study gender differences in responsiveness to price, quality and distance. Since we found no evidence of significant gender heterogeneity in response to provider quality and distance, we drop their interaction with gender in our final specification.

4.1 Random Parameter model

Table 3 investigates price, quality, and distance as determinants of health provider choice. The results from the random parameter model (columns 1 and 2) confirm that price and quality effects vary substantially across individuals. The coefficients associated with distance are fixed for tractability.[18] The estimated standard deviations of their coefficients are highly significant, with reasonable magnitudes relative to the estimated means.

The distribution of the price coefficient in the poorest quartile has an estimated mean of -0.503 and an estimated standard deviation of 0.436 (Table 3 column 1 'SD, Standard deviations').[19] Robustness tests show that using a log-normal distribution for the price coefficients yields qualitatively similar results to those obtained with the normal distribution. We discuss the magnitude of the price effects with the main results below.

Turning to the effect of quality (in columns 1 and 2), we find that individuals are more likely to choose facilities with a larger number of qualified staff and with a working

[18] When all coefficients are allowed to vary in the population, identification is empirically difficult, as explained in Ruud (1996). Models with all coefficients varying did not converge in any reasonable number of iterations, as expected.

[19] The mixed logit estimates in column (2) imply that approximately 3% of the population in the poorest quartile, 7% in the second quartile, 7% in the third quartile and 11% in the richest quartile have a positive coefficient on price. This could be an accurate representation of reality or could be an artifact of the assumption of normally distributed coefficients. For example, if for a small share of the population providers' reputation is extremely important and these people are willing to demand care at providers even when prices increase, then the results represent actual preferences. Alternatively, these results could arise because the normal distribution implies negative and positive coefficients.

generator, controlling for health facility capacity. The effect of capacity (as proxied by the number of beds) is negative. That is, for a given level of qualified staff and amenities, the average individual prefers smaller providers, although the effect varies significantly across individuals as shown by the associated standard deviations.

The effect of distance in Table 3 is non-linear: up to the median distance to health providers, individuals who plan to seek formal healthcare at a public or private facility, or from a qualified doctor, are not deterred by longer travel times. However, for providers located further than the median, distance is constraining patients' choices. Similar results were found by Bolduc et al. (1996) for rural Benin.

A comparison of the mixed logit and the conditional logit coefficients shows that the (mean) coefficients in the mixed logit are larger in absolute value than the (fixed) coefficients in the conditional logit. This is due to the fact that the error term in the conditional logit incorporates any variance in the parameters, while in the mixed logit that variance is treated explicitly, making the variance of the error term smaller compared to the conditional logit.[20] The larger magnitude also suggests that the random parameters represent a large share of the variance in unobserved utility. The fixed coefficients in the mixed logit, such as for distance, are instead directly comparable to the conditional logit coefficients. These results provide evidence of a substantial and significant heterogeneity in responsiveness to quality and price in our setting, which is more accurately captured by a random parameter model than the less flexible conditional logit.

4.2 Instrumenting prices

We allow the price to be endogenous and estimate the price instrumenting equation (5). Overall, the instruments are powerful. A stronger competition in terms of quality among health facilities (as measured by the number of doctors and beds, and generator availability at competitors, weighted by their inverse distance) and among doctors and informal providers (as measured by the number of local competitors in the village) are associated with a lower price of care. The price of treatment also increases in age and is lower for individuals in the poorest income quartile.[21] Price is significantly related to the type of illness, emphasizing the importance of taking illness heterogeneity into account. Interestingly, prices are not significantly different for men and women after

[20] In both models the parameters are normalised such that the error term has the appropriate variance for an extreme value error. Since the parameters in the mixed logit are normalised by a 'smaller error term', the mixed logit parameters are larger in magnitude than those of the conditional logit.

[21] In alternative specifications we tested age entering in a non-linear form but we do not find evidence of non-linear effects (p-value=0.185).

controlling for type of illness by gender.

We now turn to the main equation, in which we investigate the endogeneity of the price variable. Table 3 reports the estimation results for the random parameter model before instrumenting prices (column 1), and after instrumenting the price (column 2) and then also compares these results with those obtained from conditional logit models before and after instrumenting (columns 3 and 4, respectively).

The results in columns (2) and (4) show that the residuals of the control function enter the model significantly, yielding evidence that providers' prices are endogenous. The positive coefficient suggests that prices are positively correlated with unobserved heterogeneity, as could be the case with unobserved desirable attributes.

Using the RPM model, we find that price effects by income quartile are all negative and strongly significant. That is, as expected, the more expensive a provider is, the less likely individuals are to choose this alternative. We find this results both with and without instrumenting, but the coefficients are larger in magnitude when endogenous prices are controlled for.

Instead, using a conditional logit model, we find unexpected results when prices are not instrumented (column 3): price has a small and significantly negative effect on demand for individuals in the poorest income quartile, but the price effect is significantly positive for individuals in richer quartiles. This result would suggest that at a given distance and quality, individuals would prefer a provider that is more expensive. However, the conditional logit results change drastically when price is instrumented (column 4). The negative price effect for the poorest quartile increases in both magnitude and statistical significance and the price effects for the second to fourth quartiles all become negative.

With both RPM and conditional logit models, the inclusion of the control function adjusts the estimated price coefficients in the expected way: the price effect is more negative in column (2) compared to column (1) and in column (4) compared to (3), respectively. This is consistent with the interpretation that a high price reflects in part other, desirable attributes, such as reputation. Such attributes will have a positive impact on provider choice and would thus counterbalance the negative effect of price. Once the endogeneity of price is taken into account with the control function, the estimated price coefficients become more negative.[22] The positive sign on the control function's residual reinforces this interpretation. Based on these findings, we conclude that price is endogenous and should be instrumented.

[22]Similarly, the price elasticities become substantially larger as well when based on the instrumented RPM (Table 4) versus the non-instrumented RPM (Appendix Table A.2).

4.3 Main results

To quantify the magnitude of the price effect, we first compute price elasticities for the whole sample in Table 4. The own- and cross-price elasticities computed from the control function specification of the random parameters model are all significant at conventional levels, with negative and positive signs, respectively, as expected. Own price elasticity is smallest for informal care, which is cheapest on average to begin with (see Table 1). Price changes of formal care translate into substantial shifts towards alternative providers. This substitution effect is particularly strong from public care to the informal sector, suggesting that price increases in the public sector drive people out of the formal healthcare market.

Table 5 examines differences in price responsiveness between male and female patients in column (2), using our final instrumented RPM specification from Table 3 (which is repeated in column (1) for comparison). The interaction effects between price and female for a given income quartile are negative and significant for all quartiles. The estimated coefficients suggest that women are more price sensitive than men: women reduce their demand for healthcare more when prices increase.

We use these results to calculate the own- and cross-price elasticities by gender.[23] Table 6 shows that own price elasticities for all types of formal providers are substantially larger for women than for men, and significantly so at the 5 percent level for private facilities. The magnitudes of the differences are more pronounced for formal facilities than for private doctors. Different price responsiveness of men and women in turn may lead to gender gaps in healthcare utilization when the cost of formal care increases. As such, our results are in line with existing studies describing that women are disadvantaged in accessing formal types of healthcare.

In contrast to findings from other settings (e.g. Dor *et al.*, 1987; Borah, 2006; Sarma, 2009), we do not find evidence of significant differences in price elasticities across income groups. Appendix Table A.3 shows that individuals in the poorest quartile in our sample are not more price sensitive as compared to individuals in richer quartiles. One potential explanation is that our sample is relatively homogeneous and includes mostly poor people, who are all sensitive to the price charged at health providers. Inequality in Kwara state as measured by its Gini coefficient is among the lowest in the country at 0.359 compared to 0.447 at the national level (NBS, 2012). The lack of heterogeneous price effects by income quartile has also been observed in Ogun, another relatively equal Nigerian state (Akin *et al.*, 1995).

[23] There are no significant gender differences in responsiveness to quality and distance. Results available upon request.

4.4 Exploring potential mechanisms

To unpack potential reasons why women are more price sensitive, this section investigates four potential explanations.

The first possibility is that gender heterogeneity in price elasticities is simply due to men and women being affected by different types of illnesses, to which patients respond differently. The frequency of illness types differs across gender; women are more likely to suffer from febrile illnesses but less subject to severe injuries or infections than men (see Appendix Table A.4). However, heterogeneity in price coefficients across gender remains significant when interacting price, gender and type of illness in the main model (Appendix Table A.5): females are more price sensitive than males even after controlling for types of illnesses. The price-illness-gender interactions are statistically significant for febrile and other illnesses. We observe no statistically significant differences for respiratory and infectious diseases nor injuries, possibly due to a lack of power for these categories with smaller numbers of observations. These findings suggest that the gender heterogeneity in price responsiveness is not explained by different types of illnesses affecting men and women, in as much as we can observe from the data.

Second, the gender differences in access to healthcare may be related to unequal intra-household bargaining power. Following the literature on women's empowerment (Kabeer, 1999) and in line with the Nigerian descriptive evidence (Angel-Urdinola & Wodon, 2010; Kritz & Makinwa-Adebusoye, 1999), we use spousal age differentials as well as relative female income shares as proxies for female decision-making power, with cut-offs for high and low status at the sample medians. Using our main specification, we study gender heterogeneity in price responsiveness along these bargaining power dimensions instead of income. Specifically, we interact the effect of price with gender and the respective indicators for low/high bargaining power of women in the household.

Given our focus on decision-making in marital relationships, we focus on the subsample of spouses. This may give us a lower bound on female price responsiveness. Other women in the household, who are not married to the head – such as widows (Milazzo & van de Walle, 2021), may be economically more disadvantaged, have less to say in the decision-making process, and hence be even more price responsive. This pattern is expected to be reversed, however, in female-headed households (Milazzo & van de Walle, 2017).

Table 7 provides a description of patient characteristics by bargaining power status in terms of spousal age differences in column (1) and relative income shares in column (2). Panel A shows that the average spousal age difference in high bargaining households is 6.4 years compared to an average difference in low bargaining households of 17.9 years. Women in the sample are on average 43 years of age in both subsamples, so the spousal age difference reflects a husband age of 49 and 61 years in high and low bargaining households, respectively. Women with high spousal age gaps (i.e. low bargaining power) in Panel B are living in larger households with relatively more children, are lower educated and marry lower educated men compared to women with high bargaining power. Comparing Columns (1) and (2) shows that the two measures of bargaining power are not perfect substitutes, but instead capture different aspects of empowerment and decision-making. Weekly income differences between spouses are not significantly different between high and low bargaining power households in Column (1), while spousal age differences are of similar magnitude between high and low bargaining power households in Column (2) and actually somewhat larger in households where women earn relatively high weekly incomes compared to their husbands' earnings.

Table 8 disaggregates Table 6 into households where women have either high or low bargaining power, with spousal age differences and spousal weekly income differences as proxies for bargaining power in Panels A and B, respectively. The results are highly consistent across the two proxies. Regardless of how we measure bargaining power, women with low bargaining power are significantly more price responsive than their husbands for all types of formal care: public facilities, private facilities and private doctors. The differences are especially pronounced for the latter two types. Women with high bargaining power, on the other hand, do not have a differential price responsiveness for public facilities nor for private doctors compared with their spouse. However, their price elasticity remains significantly larger for healthcare at private facilities. In other words, a lack of bargaining power explains why the most disadvantaged women have lower access to public facilities and private doctors, but it cannot fully explain the general greater female price responsiveness for private facilities.

Because a large age differential may capture the more intensive healthcare needs of an old husband rather than bargaining power *per se*, we add an interaction of price and gender with the age of the husband in Appendix Table A.6 column 1. The results are robust to this inclusion. It is not the old husband requiring substantial resources that is driving the results, it is the relatively less empowered wife who cannot secure resources for herself. Column 2 interacts price and gender with the age of the wife, replicating the results from column 1. That is, potentially different healthcare needs of relatively young women do not drive the results either.

A third potential mechanism underlying the higher female price responsiveness may be related to social norms within the community that discourage women from accessing formal healthcare, for example if female mobility is restricted. In that case, long travel distances to formal health providers in combination with their higher prices may be a stronger deterrent for women compared to men.[24] Gender heterogeneity along distance, however, turns out not to be significant, suggesting that the travel distance is unlikely to drive the observed gender differences in price responsiveness.[25] Alternatively, we can investigate gender differences in price responsiveness from a religious perspective, for example if religion is correlated with restrictions in female healthcare choices. Although our findings show that Muslim individuals are more price-elastic than Christians – in line with Nigerian evidence on disadvantaged access to healthcare for Muslim populations (Ariyo *et al.*, 2017), this is true for both men and women.[26]

Finally, gender gaps in healthcare utilization may be due to some forms of discrimination on the supply side. This can be the case if, for example, formal healthcare providers charged systematically higher prices to women versus men for the same type of illness, which could in turn induce women to forego expensive formal healthcare. The descriptive evidence suggests the opposite: men pay higher prices on average. Note that this may reflect a gender bias in terms of quality of care, to the extent that higher-quality treatment is often more expensive (e.g. in terms of medicines or diagnostics). Perhaps men are better positioned to request good-quality treatment for their illness, or instead providers may adjust their services to patients' gender. We do not have the appropriate data in our dataset to further investigate supply-side discrimination.

5 Predictions and policy implications

The distinct advantage of structurally modeling health-seeking behavior is that it allows to predict ex-ante how individuals will respond to certain policies, at least to the extent that the model captures well enough the heterogeneous responses by individuals in the real world. This section will dive deeper into such policy implications.

In particular, we will first examine the predicted effects of price subsidies – either in the public sector only or in the public and private sector combined – on utilization at different provider types for the population under study. This will for example mimic the implications of subsidies to national health insurance schemes that are now widely discussed as a key pre-payment and risk-pooling mechanism to improve Universal Health Coverage (e.g. Lagomarsino *et al.*, 2012). Next, the structural estimates of heterogeneous determinants of provider choice enable us to analyse the distributional

[24] As a comparison, see Jayachandran (2015) for evidence on the link between distance and girls' schooling.
[25] Results available upon request.
[26] Idem.

impacts of price subsidies on access to healthcare by men and women.

5.1 Price subsidies for the public and private sector

The results of our policy simulations are presented in Table 9. Panel A examines the predicted impacts on the population under study. The first two columns present the status-quo: the observed probability that an ill person chooses each provider type in Column (1) and the associated predicted probability from our preferred specification in Column (2). Reassuringly, the estimates based on the structural model accurately capture the actual utilization rates of each provider type.

We simulate the impacts of a price subsidy that reduces the price of care in the formal public sector to zero in Column (3). This could represent for example a government policy of free public care, or a fully subsidized government insurance scheme that only covers care at public facilities. We proceed as follows. We put the prices at all public health facilities artificially to zero, while leaving all other provider characteristics (location, quality) as well as individual characteristics constant. Next, using the estimates of the RPM with control function in Table 3 Column (2), we run the model on the artificial dataset to predict provider choices and calculate demand by provider type.

The results in Column (3) indicate that a large shift towards the public sector can be expected from a full public sector price subsidy, from an average predicted utilization of 36.7% in the original situation to 86.5%. The more than doubling of formal public care utilization is accounted for by a decrease across the board in the utilization of other provider types. The shift away from informal care is largest, from 30.1% to 4.4%. Patients also move from the private to the (now free) public sector, reducing private demand from 24.6% to 7.3%. Finally, the probability that an ill individual will seek care at a private doctor reduces from 8.4% to 1.7% when public facilities become free.

A note of caution is warranted here. This simulation does *not* take into account second-order effects. Unless capacity is vastly increased, this policy is likely to lead to overcrowding and understaffing at public facilities, which will attenuate the positive effects on access to formal care. To account for such unintended side-effects, our predictions would benefit from additional information on 'softer' aspects of provider quality such as waiting times and staff attitudes (Alhassan *et al.*, 2015), which is not included in our dataset. If human resources or amenities are insufficient to accommodate the greater inflow of patients, this will put downward pressure on demand. Demand for public care will stabilize in the medium-term at a new equilibrium that balances both mechanisms.

Taking into account potential public sector capacity constraints, another interesting exercise is to simulate the policy effects of a price subsidy not only in the public but also in the private sector – which would presumably reduce pressure on public resources. Such a simulation captures for example the impacts of a national insurance scheme that covers both public and private providers, which is in line with new government plans in Kwara to roll out a State-wide insurance scheme that also encompasses the private sector (Akande, 2019). Table 9 Column (4) shows the results. In line with expectations, this more comprehensive policy is predicted to shift part of the increase in public care back towards the private sector, with subsequent utilization rates of 58.6% and 38.2%, respectively.

Nevertheless, and perhaps surprisingly, the demand for public care remains well above the demand for private care. Differences in quality or geographical accessibility between public and private facilities might provide an explanation, as these are important determinants of healthcare choices as well. Indeed, a closer look at the underlying provider characteristics reveals that private care is not necessarily of higher quality than public care, but rather shows a bimodal distribution in terms of amenities (as proxied for by generator availability in Table 1) and number of qualified doctors, similar to public clinics (see Appendix Figures A.1 and A.2). Whereas some private clinics are of high quality, others offer care that is in fact of lower quality than in the average public clinic. The preference for public clinics has also been documented in other Nigerian studies (Oredola & Odusanya, 2017). We note that the average distance to public providers tends to be larger than to private facilities. That is, differential geographical access cannot explain the greater demand for public care.

Overall, the utilization rate of public and private clinics combined is predicted to increase substantially from 61.3% in the status-quo to 93.8% or even 96.8% depending on whether the price subsidy covers only the public sector or both the public and private sector.

5.2 Heterogeneous impacts by gender

We now extend the previous simulations and disaggregate the predicted effects for men and women. A priori it is not obvious in which direction the price subsidy would affect the gender gap in formal care utilization. On the one hand, women are significantly more responsive to price changes, which should increase their access to formal care disproportionately. On the other hand, women face lower prices to begin with (Table

2) — potentially reflecting the lower quality of services they receive, such that a full price subsidy would have a relatively lower impact on their formal healthcare demand.

Table 9 shows the status quo and the policy simulations as before, disaggregated by gender: Panel B for men and panel C for women. The male and female predicted probabilities of accessing public and private clinics at status quo are 64.3% and 60.1%, respectively (Column 2), representing a gap of 4.2 percentage points. This is smaller than the observed gap in the utilization of formal care. More specifically, female utilization of formal care is overpredicted while for men it is slightly underpredicted, indicating that our model does not capture the disadvantaged access for women to formal care to its full extent.

Column (3) shows that a full price subsidy in the public sector would increase formal care utilization among men to 94.4% and among women to 93.8%, almost lifting the predicted gender gap. A full price subsidy in both the public and private sector further increases access to private and public clinics to 96.8% and 96.9% for men and women, respectively, fully compensating for the initial gender gap (Column 4).

In other words, the findings show that a price subsidy is expected to have a larger effect on female demand for formal care than on male demand due to the higher price responsiveness of women. A price subsidy that completely eliminates user fees will also eliminate gender bias in access to healthcare in this context, at least to the extent that it is captured in our structural model.

6 Conclusions

This paper develops a structural model of health-seeking behavior in a resource-limited setting, using data on poor rural households in Nigeria, and uses the model to subsequently simulate how various health system interventions would increase formal health care utilization for the total population, as well as for women and men separately.

The findings show that price, quality and distance are strong determinants of health provider choice, in line with previous studies in other settings and (descriptive) evidence from Nigeria (Stock, 1983; Akin *et al.*, 1995; Onwujekwe, 2005). High prices act as a significant deterrent to formal health care utilization. Accessibility in terms of distance is also a crucial factor in the choice of seeking care, which underscores the importance of increasing outreach to rural and remote areas. Finally, people consistently search for better quality: the higher the number of qualified doctors for a given size and the better the amenities as proxied by a functioning generator, the more likely it is that a patient will choose a particular health care provider.

The results are highly sensitive to the instrumentation of price. Not controlling for the endogeneity of price leads to unexpected results when using standard logit models, or drastically alters the conclusions when using more flexible models such as Mixed Logit models, allowing for heterogeneity in price coefficients. As a result, not addressing this econometric issue may lead to unfounded policy recommendations.

We find that women in our sample are significantly more likely than men to forego formal health care when prices increase. The different types of illnesses affecting male and female patients cannot explain these gender differences alone. Instead, we find suggestive evidence that gender heterogeneity in price responsiveness may be due to intra-household decision-making processes, as women with low bargaining power in the household are more price sensitive than others. These findings offer one explanation for the gender bias in accces to quality health care.

Our results illustrate the importance of carefully modeling health care provider choices for improved health programming. First, identifying the specific individual, household and facility characteristics that determine current patterns of health-seeking behavior yields insights in the reasons why different groups of people choose particular types of providers for treatment of particular types of illnesses. This knowledge will be useful to improve targeting of interventions to specific subsamples in the population and to particular provider types. Given the continuously high reliance of the Nigerian health system on out-of-pocket expenditures that are steadily increasing over time and result in high prevalence of catastrophic health spending (Ejughemre, 2014; Onoka *et al.*, 2011), our findings underscore that women may lose even further due to bad health in the future in the absence of well-designed subsidies and interventions.

Secondly, assessing how patients respond to changes in direct costs, indirect costs and quality of service may inform policy about expected movements of patients between providers that belong to the public or private market and outside the formal market (i.e. informal and self-care). The distinction between men versus women is important in this respect. In our setting of very poor households living in rural and underserved areas, we find that subsidizing the price of public care significantly increases formal health care utilization, especially among women. In fact, such a price subsidy is predicted to eliminate gender differences in access to care. Our findings suggest that – because of the high female price responsiveness – subsidies to health insurance are expected to affect women more than men, and, from this viewpoint, may allow to compensate for the gender gap in health care coverage. The recent announcement of a state-wide subsidized health insurance scheme in Kwara State may bring the necessary alleviation in this respect (Akande, 2019).

Thirdly, our model allows us to evaluate the relative importance of the key mechanisms at play, which can shed light on the complex policy impacts to be expected in resource-limited setting. Subsiding public care is predicted to substantially boost the demand for formal care. When such subsidies are not accompanied by a concomitant increase in capacity of public facilities, this may create a backlash in terms of overcrowding, reducing public demand (and potentially public quality) in the longer run (see also Kondo & Shigeoka, 2013). Incorporating the private sector might be a good solution in poor settings to make full use of existing resources. Extending our model to better capture such dynamic effects and the impact of public-private interactions is left for future work.

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Table 1: Patient and provider characteristics by type of provider

	all	informal	public	private	doctor
A. Patient characteristics					
N	1,701	526	592	434	149
female (%)	0.52	0.57	0.48	0.49	0.56
age	31.5	31.4	32.8	32.0	27.5
spousal age diff. (age head -/- age spouse)	10.23	10.48	10.92	9.26	9.78
hh size	5.3	5.4	4.9	5.4	5.5
schooling (years)	4.73	3.88	5.28	5.01	4.75
schooling (years, male)	5.65	5.21	5.95	5.88	4.94
schooling (years, female)	3.89	2.89	4.58	4.10	4.62
mean aggr. consumption (1,000 NAIRA)	409	371	420	453	368
median aggr. consumption (1,000 NAIRA)	324	291	322	352	303
provider choice (%)		30.9	34.8	25.5	8.8
provider choice by female (%)		34.3	32.1	24.1	9.5
provider choice by male (%)		27.5	37.3	27.2	8.0
febrile illnesses (54.0%)		35.5	31.5	22.2	10.7
infections/ pains (5.5%)		27.1	35.8	31.5	5.4
respiratory diseases (3.2%)		30.7	34.6	30.7	3.8
accidents/injury (2.5%)		21.4	35.7	38.0	4.7
others/ unknown (34.5%)		25.1	39.3	28.5	7.0
		informal	public	private	doctor
B. Provider characteristics					
mean price (observed, NAIRA)		934	4786†	2965†	1692
median price (observed, NAIRA)		603	2366	2586	879
standard deviation price (observed, NAIRA)		753	5325	1632	1360
mean price (imputed, NAIRA)[a]		1009	3518	3530	2016
median price (imputed, NAIRA)[a]		603	1260	2586	879
number of doctors[b]		0	1.2	1.4	1
number of beds[b]		0	32.5	8.8	0
no generator (%)[b]		100	30	37	100
sometimes (%)		0	46	0	0
most of the times (%)		0	0	50	0
always (%)		0	23	12	0

The tables shows the patient and provider descriptive statistics by type of provider. † figure exclude a small number of outliers. [a]: The price of a health provider is imputed as the average price paid by individuals attending the same provider and affected by the same illness. Four outliers observation for price are excluded. [b]: The number of doctors and beds, and generator availability are imputed for categories informal and doctor.

Table 2: Price instrumenting equation

is a health facility	5084.105***
	(116.013)
is a private doctor	-1026.056***
	(70.836)
competitors' number of doctors	-267.535***
	(10.348)
competitors' number of doctors (squared)	8.496***
	(0.353)
competitors' generators	-267.363***
	(12.872)
competitors' generators (squared)	7.778***
	(0.247)
competitors' number of beds	-19.691***
	(0.731)
local competitors	-1.901
	(4.856)
distance village-nearest facility	-9.106*
X is a private doctor	(4.796)
female	-16.962
	(10.453)
age	2.488***
	(0.854)
illness type 2	4033.231***
	(24.810)
illness type 3	6088.221***
	(47.848)
illness type 4	5932.687***
	(98.669)
illness type 5	2841.654***
	(61.168)
income q2	83.502***
	(29.582)
income q3	108.304**
	(51.561)
income q4	85.433***
	(30.233)
illness type 2 X female	54.093*
	(29.945)
illness type 3 X female	-24.619
	(56.879)
illness type 4 X female	-272.222
	(187.946)
illness type 5 X female	-85.120
	(72.866)
constant	352.338***
	(80.726)
N	39721
R2	0.116
MLL	-405729
Average Marginal Effects	
Competitors' num doctors	-181.7
Competitors' generators	-117.1
Competitors' num beds	-19.7

The table shows the regression estimates of the equation instrumenting the price (equation 1). 'Competitors number of doctors', 'competitors generator' and 'competitors number of beds' are quality indicators from the health facilities competitors (weighted by the inverse distance). 'Local competitors' indicates the number of private doctors and traditional healers operating in the locality. Standard errors (in parentheses) are clustered at the individual level. Average marginal effects are the average of marginal effects calculated at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: Models of health provider choice

	RPM uninstrumented		RPM control function		CL uninstrumented	CL control function
	Mean	SD	Mean	SD		
	(1)		(2)		(3)	(4)
distance	0.281***		0.305***		0.292***	0.300***
	(0.028)		(0.035)		(0.030)	(0.032)
distance (squared)	-0.004 ***		-0.005 ***		-0.005***	-0.005***
	(0.000)		(0.000)		(0.000)	(0.000)
alternative: public	-6.294***		-5.571***		-6.626***	-5.995***
	(0.490)		(0.567)		(0.522)	(0.530)
alternative: private	-6.099***		-5.172***		-6.661***	-6.065***
	(0.487)		(0.564)		(0.515)	(0.524)
alternative: doctor	-4.898***		-4.443***		-5.342***	-4.931***
	(0.536)		(0.627)		(0.560)	(0.582)
num doctors	0.158***	0.012	0.078**	0.012	0.020	0.010
	(0.052)	(0.015)	(0.038)	(0.016)	(0.030)	(0.028)
generator	0.346***	0.003	0.622***	0.010*	0.242***	0.459***
	(0.051)	(0.009)	(0.060)	(0.010)	(0.040)	(0.050)
beds	-0.019**	0.018***	-0.011	0.017***	-0.005**	0.001
	(0.008)	(0.005)	(0.009)	(0.006)	(0.002)	(0.001)
price X q1	-0.503***	0.436***	-1.261***	0.568***	-0.025	-0.495***
	(0.161)	(0.131)	(0.154)	(0.104)	(0.020)	(0.044)
price X q2	-0.656***	0.643***	-1.571***	0.752***	0.012*	-0.481***
	(0.147)	(0.139)	(0.175)	(0.105)	(0.007)	(0.044)
price X q3	-0.851***	0.727***	-1.677***	1.065***	0.013***	-0.479***
	(0.130)	(0.106)	(0.158)	(0.128)	(0.005)	(0.043)
price X q4	-0.800***	0.870***	-1.512***	1.087***	0.021***	-0.471***
	(0.187)	(0.179)	(0.162)	(0.158)	(0.006)	(0.044)
Residual CF			0.591***			0.421***
			(0.057)			(0.037)
Residual CF (squared)			-0.002***			0.001***
			(0.000)			(0.000)
N	39,100		39,100		39,100	39,100
MLL	-4,088		-3,888		-4,253	-4,121

The table presents different model estimates for the demand for health care: the Random Parameter Model estimates with endogenous price (RPM uninstrumented); the Random Parameter Model estimates using the control function for price (RPM instrumented); the Conditional Logit estimates with endogenous price (CL uninstrumented) and the Conditional Logit estimates with control function (CL instrumented). Variables are defined as follows: distance is the kilometric distance between the household dwelling and each provider (and its square); variables with the prefix 'alternative:' indicates dummy variables for provider types (public, private and doctor), the omitted variable is informal care; 'num doctors' indicates the number of doctors at each provider; 'generator' indicates the quality of electric generator at the provider; 'beds' indicates the number of beds at the provider; variables 'price X q♯' indicate interactions terms between the price paid and an indicator for ♯ quartile of household income; 'residual CF' indicates the residual of the price control function (and its square). In each model, standard errors are clustered at the household level and estimated by bootstrapping (500 replications). * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4: Demand responses to changes in price

Price elasticities of demand for a 1% change in price in i				
(i,j)	Informal	Public	Private	doctors
informal	**-1.114**	0.312	0.260	0.332
	(0.077)	(0.018)	(0.016)	(0.018)
public	0.470	**-1.358**	0.358	0.470
	(0.031)	(0.472)	(0.079)	(0.053)
private	0.426	0.436	**-1.578**	0.602
	(0.042)	(0.080)	(0.153)	(0.057)
doctors	0.159	0.129	0.126	**-2.084**
	(0.016)	(0.013)	(0.014)	(0.142)

The table presents the demand responses to changes in price. The elasticities are the average percentage change in the demand of alternative j (column) given 1% change in price. For each provider i, figures in each row are the elasticities'/demand change point estimates; figures in parentheses are bootstrapped standard errors (estimated by the standard deviations of the empirical distributions of estimated elasticities/demand change bootstrapped with 100 replications).

Table 5: Health Provider Choice (RPM): Heterogeneity by gender

	MAIN MODEL		MAIN MODEL BY GENDER	
	Mean	SD	Mean	SD
	(1)		(2)	
distance	0.305***		0.306***	
	(0.035)		(0.034)	
distance (squared)	-0.005***		-0.005***	
	(0.000)		(0.001)	
alternative: public	-5.571***		-5.581***	
	(0.567)		(0.557)	
alternative: private	-5.172***		-5.164***	
	(0.564)		(0.557)	
alternative: doctors	-4.443***		-4.435***	
	(0.627)		(0.622)	
num doctors	0.078**	0.034	0.071*	0.010
	(0.038)	(0.059)	(0.038)	(0.029)
generator	0.622***	0.007	0.616***	0.000
	(0.060)	(0.011)	(0.060)	(0.008)
beds	-0.011	0.015*	-0.009	0.016***
	(0.009)	(0.008)	(0.008)	(0.005)
priceXq1	-1.261***	0.392***	-1.107***	0.532***
	(0.154)	(0.133)	(0.173)	(0.133)
priceXq2	-1.571***	0.615***	-1.349***	0.930***
	(0.175)	(0.150)	(0.170)	(0.153)
priceXq3	-1.677***	0.751***	-1.521***	1.175***
	(0.158)	(0.134)	(0.159)	(0.151)
priceXq4	-1.512***	0.824***	-1.474***	1.180***
	(0.162)	(0.235)	(0.161)	(0.174)
priceXq1 X female			-1.407**	0.654
			(0.184)	(0.116)
priceXq2 X female			-1.800***	0.974
			(0.211)	(0.137)
priceXq3 X female			-1.763***	0.915***
			(0.181)	(0.115)
priceXq4 X female			-1.647***	1.075***
			(0.220)	(0.184)
residual CF	0.591***		0.588***	
	(0.057)		(0.042)	
residual CF (squared)	-0.002***		-0.003***	
	(0.000)		(0.000)	
N	39100		39100	
MLL	-3,888		-3,875	

The table shows the Random Parameter Model estimates for the demand of health care allowing for heterogeneous responsiveness to price by gender. Bootstrapped standard errors are in parenthesis and are estimated using 500 replications. Variables with X indicate interactions terms between the lowercase variables. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Price elasticity by gender

	Male					Female			
(i,j)	**Informal**	**Public**	**Private**	**doctors**	**(i,j)**	**Informal**	**Public**	**Private**	**Doctors**
Informal	**-0.954**	0.281	0.250	0.270	**Informal**	**-0.943**	0.290	0.261	0.299
	(0.113)	(0.0231)	(.018)	(.021)		(.116)	(.022)	(.017)	(.023)
						[40%]			
Public	0.492	**-1.207**	0.477	0.558	**Public**	0.487	**-1.318**	0.471	0.539
	(.319)	(.303)	(.351)	(.329)		(.392)	(.283)	(.422)	(.404)
							[79%]		
Private	0.497	0.499	**-1.549**	0.623	**Private**	0.443	0.460	**-1.736**	0.559
	(.083)	(.127)	(.174)	(.079)		(.042)	(.078)	(.158)	(.054)
								[95%]	
Doctors	0.122	0.109	0.112	**-1.939**	**Doctors**	0.127	0.111	0.114	**-1.978**
	(.017)	(.014)	(.015)	(.183)		(.017)	(.014)	(.014)	(.170)
									[61%]

The table reports the (average) price elasticities of demand by gender. The elasticity are the percentage change in probability for alternative j (column) given 1% change in price in i (row). For each provider i, figures represent (i) point estimate in the first row (ii) bootstrapped standard errors in parentheses in second row (these are computed as the standard deviations of the empirical distributions of the elasticities calculated in 100 bootstrapped 100 samples); (iii) in squared brackets, the probability to observe women having smaller elasticities (i.e. more negative) than men in 100 bootstrapped samples.

Table 7: Patient characteristics by bargaining power status & by type of provider (averages, spouse sample)

	Age differences between spouses	Weekly income differences between spouses
High Bargaining households		
N	389	327
spouse age diff. (head - spouse)	6.43***	11.01**
weekly income diff. (head - spouse)	2230	-960***
age husband	49.05***	56.77***
age wife	42.62	46.31***
hh size	5.0*	4.48**
number of children	2.51	2.12**
schooling (years)	4.91***	3.75***
schooling (years, male)	5.72***	4.10***
schooling (years, female)	4.12***	3.29
Low Bargaining households		
N	204	369
spousal age diff. (age head -/- age spouse)	17.88	9.80
weekly income diff. (head - spouse)	2124	5329
age husband	60.76	48.34
age wife	42.87	39.29
hh size	5.2	4.85
number of children	2.72	2.46
schooling (years)	3.09	5.44
schooling (years, male)	3.77	6.60
schooling (years, female)	2.35	3.91

The table shows the patient sample characteristics by high and low bargaining status. Households are classified as having high (low) bargaining power household in two ways: i. if the age differential between the husband and the wife is lower (higher) then the median differential in the sample (column age differences); ii. if the weekly income differential between the husband and the wife is lower (higher) then the median differential in the sample. Stars in the first column indicates that the average in high vs. low bargaining status households is statistically significant (t-test, *<0.10 **<0.05 ***<0.001).

Table 8: Price elasticities by bargaining power status and gender

PANEL A. High bargaining status: small age differences

	Male					Female			
(i,j)	**Informal**	**Public**	**Private**	**doctors**	**(i,j)**	**Informal**	**Public**	**Private**	**Doctors**
Informal	**-0.334**	0.109	0.109	0.109	**Informal**	**-0.456**	0.182	0.187	0.187
	(0.258)	(0.086)	(.069)	(.077)		(.256)	(.051)	(.040)	(.051)
						[98%]			
Public	0.828	**-1.002**	0.831	0.828	**Public**	1.026	**-0.707**	1.030	1.026
	(.241)	(.196)	(.241)	(.233)		(.792)	(.663)	(.797)	(.782)
							[56%]		
Private	1.331	1.329	**-0.470**	1.331	**Private**	0.512	0.508	**-1.736**	0.512
	(.423)	(.446)	(.467)	(.387)		(.074)	(.081)	(.218)	(.076)
								[92%]	
Doctors	0.125	0.124	0.124	**-1.077**	**Doctors**	0.072	0.068	0.072	**-0.819**
	(.049)	(.050)	(.051)	(.398)		(.026)	(.019)	(.018)	(.465)
									[29%]

Low bargaining status: large age differences

	Male					Female			
(i,j)	**Informal**	**Public**	**Private**	**doctors**	**(i,j)**	**Informal**	**Public**	**Private**	**Doctors**
Informal	**-0.477**	0.237	0.239	0.239	**Informal**	**-0.630**	0.348	0.265	0.317
	(0.279)	(0.069)	(.068)	(.069)		(.211)	(.051)	(.037)	(.047)
						[56%]			
Public	0.751	**-0.948**	0.754	0.751	**Public**	0.364	**-0.970**	0.476	0.539
	(.200)	(.179)	(.211)	(.196)		(.051)	(.138)	(.054)	(.049)
							[95%]		
Private	1.251	1.249	**-0.764**	1.250	**Private**	0.327	0.498	**-1.415**	0.447
	(.326)	(.370)	(.314)	(.294)		(.061)	(.054)	(.204)	(.106)
								[98%]	
Doctors	0.079	0.078	0.078	**-0.979**	**Doctors**	0.044	0.198	0.119	**-1.335**
	(.020)	(.016)	(.018)	(.415)		(.020)	(.016)	(.019)	(.357)
									[90%]

PANEL B. High bargaining status: small weekly income differences

	Male					Female			
(i,j)	**Informal**	**Public**	**Private**	**doctors**	**(i,j)**	**Informal**	**Public**	**Private**	**Doctors**
Informal	**-0.362**	0.107	0.108	0.107	**Informal**	**-0.577**	0.344	0.261	0.271
	(0.220)	(0.069)	(.058)	(.064)		(.195)	(.045)	(.042)	(.045)
						[97%]			
Public	0.920	**-0.988**	0.921	0.920	**Public**	1.184	**-0.459**	1.200	1.167
	(.237)	(.153)	(.228)	(.222)		(.732)	(.664)	(.745)	(.731)
							[75%]		
Private	1.268	1.267	**-0.587**	1.267	**Private**	0.491	0.588	**-1.401**	0.424
	(.354)	(.373)	(.363)	(.329)		(.072)	(.092)	(.193)	(.079)
								[100%]	
Doctors	0.117	0.117	0.117	**-1.124**	**Doctors**	0.114	0.179	0.102	**-1.229**
	(.038)	(.040)	(.040)	(.364)		(.022)	(.017)	(.017)	(.345)
									[69%]

Low bargaining status: large weekly income differences

	Male					Female			
(i,j)	**Informal**	**Public**	**Private**	**doctors**	**(i,j)**	**Informal**	**Public**	**Private**	**Doctors**
Informal	**-0.500**	0.242	0.241	0.241	**Informal**	**-0.484**	0.233	0.142	0.191
	(0.244)	(0.077)	(.077)	(.077)		(.209)	(.054)	(.044)	(.053)
						[57%]			
Public	0.823	**-0.950**	0.823	0.823	**Public**	0.536	**-1.161**	0.434	0.496
	(.208)	(.142)	(.211)	(.202)		(.052)	(.121)	(.069)	(.061)
							[98%]		
Private	1.165	1.165	**-0.915**	1.165	**Private**	0.447	0.438	**-1.294**	0.372
	(.295)	(.334)	(.248)	(.269)		(.052)	(.058)	(.236)	(.084)
								[94%]	
Doctors	0.075	0.075	0.074	**-1.022**	**Doctors**	0.129	0.099	0.011	**-1.224**
	(.019)	(.016)	(.018)	(.395)		(.022)	(.016)	(.019)	(.413)
									[86%]

The table reports the (average) price elasticities of demand by gender. The elasticity are the percentage change in probability for alternative j (column) given 1% change in price in i (row). For each provider i, figures represent (i) point estimate in the first row (ii) bootstrapped standard errors in parentheses in second row (these are computed as the standard deviations of the empirical distributions of the elasticities calculated in 100 bootstrapped 100 samples); (iii) in squared brackets, the probability to observe women having smaller elasticities (i.e. more negative) than men in 100 bootstrapped samples.

Table 9: Policy simulations

	Status quo		Price interventions	
	(1)	(2)	(3)	(4)
Provider	**Observed probability**	**Predicted probability**	**Price subsidy** in Public sector only	**Price subsidy** in Public & Private sector
Panel A. All				
1. Informal	.309	.301	.044	.021
		(.024)	(.018)	(.030)
2. Public	.348	.367	.865	.586
		(.028)	(.053)	(.076)
3. Private	.255	.246	.073	.382
		(.025)	(.025)	(.058)
4. Doctors	.088	.084	.017	.009
		(.015)	(.007)	(.010)
Panel B. Male				
1. Informal	.273	.279	.039	.021
		(.025)	(.033)	(.028)
2. Public	.375	.389	.855	.596
		(.029)	(.087)	(.088)
3. Private	.272	.254	.089	.372
		(.025)	(.037)	(.058)
4. Doctors	.080	.080	.016	.010
		(.015)	(.013)	(.012)
Panel C. Female				
1. Informal	.343	.313	.044	.021
		(.034)	(.032)	(.025)
2. Public	.321	.363	.874	.589
		(.033)	(.073)	(.076)
3. Private	.241	.238	.064	.380
		(.027)	(.027)	(.055)
4. Doctors	.095	.085	.017	.009
		(.016)	(.010)	(.008)

The table reports the simulated health care demand for different policy interventions: a price subsidy that reduces the price to zero in the Public sector exclusively (column 3) or in both the Public and Private sector (columns 4). Panel A uses the model estimated in Table 3, column 2; Panel B and C use the model with gender and price interactions estimated in Table 5, column 2. The standard errors (reported in parenthesis) are calculated by estimating demand changes in 100 bootstrapped samples of size n=1,000.

Appendix A

Mixed logit model estimation

This Appendix provides details on the estimation procedures of the Mixed Logit model, in the simple case when utility is linear and can be written as:

$$U_{ij} = \beta_i' x_{ij} + \epsilon_{ij}, \tag{2}$$

where x_{ij} is a vector of provider characteristics that vary across alternatives and may vary across individuals, including price, quality of care and provider's distance from the individual home; β_i is $\beta_i = \beta + \eta_i$, where β is the population mean and η_i is the stochastic deviation that represents the patient's tastes relative to the average tastes in the population. Then, $U_{ij} = \beta' x_{ij} + \eta_i' x_{ij} + \epsilon_{ij}$. The last two terms are the stochastic portion of the utility and, differently from standard logit, they are in general correlated between alternatives due to the common influence of η_i.

The probability of choosing alternative j conditional on β_i is

$$L_{ij} = \frac{e^{\beta_i' x_{ij}}}{\sum_l e^{\beta_i' x_{il}}} \tag{3}$$

The unconditional probability is the integral of the conditional probability over all possible values of β_i:

$$P_{ij} = \int L_{ij} f(\beta_i) d\beta_i \tag{4}$$

Upon specifying a distribution for the coefficients (e.g. normal or log-normal), the parameters of that distribution (such as the mean and standard deviation of β) can be estimated. Let us define these parameters as θ. The unconditional probabilities can be approximated through simulations: for a given value of the distribution's parameters θ, a value of β_i is drawn from distribution $f(\beta|\theta)$ and, for each draw, the logit formula is calculated. This process is repeated many times and the results are averaged. The average of the logit probability over draws is taken as the simulated probability for each patient i choosing provider j. These simulated probabilities, defined P_{ij}, are inserted into the log-likelihood function:

$$SLL = \sum_{i=1}^{N} \sum_{j=1}^{J} d_{ij} ln P_{ij} \tag{5}$$

where $d_{ij} = 1$ if i chooses j and zero otherwise. The maximum simulated likelihood estimator is the value of θ that maximizes the log-likelihood function. [27]

[27] We refer to Train (2001) for a more detailed exposition on mixed logit estimation procedures.

Appendix B

Calculation of price elasticities' standard errors in RPM models

The price elasticity of demand is the percentage change in demand due to a 1% change in price. Using the notation of the RPM model in Section 3, the elasticity is $\frac{P_{ij}^1 - P_{ij}^0}{P_{ij}^0}$, where P_{ij}^0 is the (conditional) probability of choosing alternative j before the price change and P_{ij}^1 is the (conditional) probability of choosing alternative j after the price change.

We calculate the elasticity standard errors using a bootstrapping procedure as follows:.

(i) Given our data of sample size N, we draw a random sample of patients of size $\tilde{N} < N$.

(ii) We estimate the model coefficients using the random sample in (i) and predict P_{ij}^0.

(iii) We then change the price by 1%, and re-estimate the predicted probabilities P_{ij}^1 after the price change.

(iv) We compute the elasticity, $\frac{P_{ij}^1 - P_{ij}^0}{P_{ij}^0}$, using the two estimated predicted probabilities.

(v) We repeat steps (i) to (iv) 100 times and obtain 100 bootstrapped estimates of the elasticity.

(vi) The bootstrapped standard error of the elasticity is the standard deviation of the empirical distribution of the bootstrapped elasticities obtained in point (v).

Appendix C. Figures

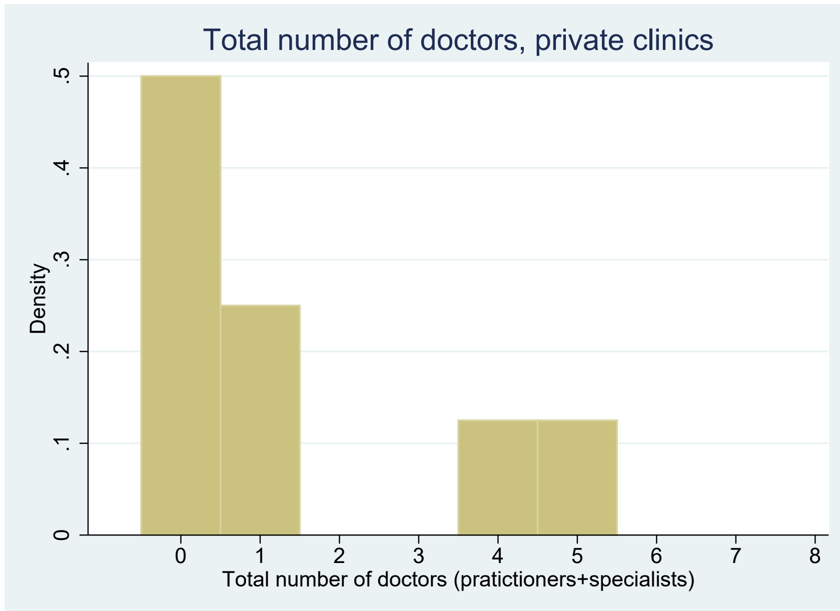

Figure 1: Total number of doctors in private facilities

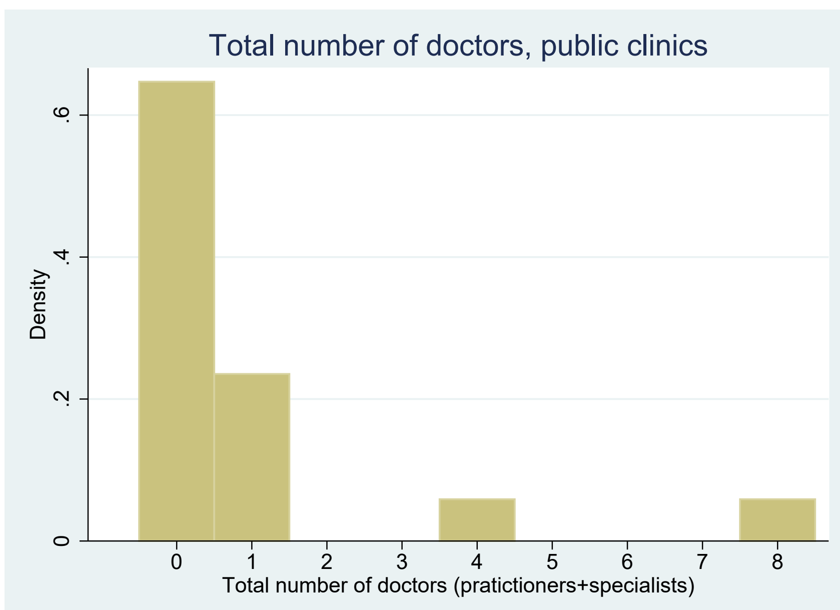

Figure 2: Total number of doctors in public facilities

Appendix D. Tables

Table A.1: Summary Statistics - Full sample and patient sample

Summary statistics of full sample						Summary statistics of patient sample					
Variable	Obs	Mean	Std	Min	Max	Variable	Obs	Mean	Std	Min	Max
female (%)	5,970	0.51	0.50	0	1	female (%)	1,701	0.51	0.50	0	1
age†	5,958	26.44	22.68	0	98	age	1,696	31.24	23.84	0	98
age ratio (hh head/spouse)	4,811	1.26	0.27	0.63	6.25	age ratio (hh head/spouse)	1,374	1.24	0.31	1	6.25
age differential (head -/- spouse)†	4,451	10.45	6.40	0	40.5	age differential (head -/- spouse)	1,216	10.23	6.52	1	40
hh size	5,970	5.55	2.71	1	16	hh size	1,701	5.25	2.72	1	14
ethnicity (Yoruba)	5,978	0.80	0.39	0	1	ethnicity (Yoruba)	1,701	0.81	0.38	0	1
religion (Muslim)	5,965	0.79	0.40	0	1	religion (Muslim)	1,701	0.79	0.40	0	1
completed schooling (years, adult male)	1,376	6.06	5.69	0	25	completed schooling (years, adult male)	459	6.08	5.74	0	25
completed schooling (years, adult female)	1,633	3.67	5.00	0	16	completed schooling (years, adult female)	567	3.68	5.14	0	16
annual hh consum. (1,000 NAIRA)	5,978	405.53	315.63	35.87	2,953.70	annual hh consum. (1,000 NAIRA)	1,700	408.64	316.68	35.87	2,671.34
spouses' weekly income difference (NAIRA)	5,622	2513	17,676	-417,143	135,600	spouses' weekly income difference (NAIRA)	1,545	2,080	14,261	-417,143	117,100

Notes: The table reports descriptive statistics of the full (representative) sample of Nigerians in Kwara and the descriptive statistics of the acute illnesses patient sample (empirical sample for models in Section 4 and 5).

† we removed the following outlier observations. Age: 10 and 5 outliers are removed from the full and patient sample, respectively. Age differential: 4 outlier observations coming from the same household in the full sample.

Table A.2: DEMAND RESPONSES TO CHANGES IN PRICE, UN-INSTRUMENTED MODEL

Panel A: Price elasticities of demand for a 1% change in price in i				
(i,j)	Informal	Public	Private	doctors
informal	**-0.439**	0.142	0.118	0.136
	(0.086)	(0.023)	(0.019)	(0.022)
public	0.217	**-0.484**	0.007	0.125
	(0.042)	(0.098)	(0.027)	(0.032)
private	0.176	0.087	**-0.642**	0.140
	(0.035)	(0.028)	(0.124)	(0.032)
doctors	0.061	0.045	0.042	**-0.804**
	(0.013)	(0.010)	(0.009)	(0.145)

The table presents the demand responses to changes in price in an un-instrumented Random Parameter Model (without control functions). The model include all control variables included in models in Table 4 except for the residual control function and its squared. The elasticities are the average percentage change in the demand of alternative j (column) given 1% change in price in i (row). For each provider i, figures in each row are the elasticities' point estimates; figures in parentheses are bootstrapped standard errors (estimated by the standard deviations of the empirical distributions of estimated elasticities/demand change bootstrapped with 100 replications).

Table A.3: Demand responses to changes in price by income quartiles

Price elasticities of demand for a 1% change in price in i				
	Q1	Q2	Q3	Q4
Informal	-0.828	-0.935	-0.974	-1.022
	(0.086)	(0.091)	(0.101)	(0.114)
Public	-1.328	-1.356	-1.308	-1.219
	(0.156)	(0.125)	(0.171)	(0.152)
Private	-1.772	-1.816	-1.564	-1.586
	(0.198)	(0.166)	(0.161)	(0.210)
Doctor	-1.952	-1.967	-1.916	-2.073
	(0.183)	(0.141)	(0.158)	(0.213)

The table reports the (average) price elasticities of demand by income quartile. The elasticity are the percentage change in probability for income quartile j (column) given 1% change in price in i (row). For each provider i, figures represent (i) point estimate in the first row (ii) bootstrapped standard errors in parentheses in second row (these are computed as the standard deviations of the empirical distributions of the elasticities calculated in 100 bootstrapped 100 samples).

Table A.4: Prevalence of illnesses by gender

Prevalence of illnesses by gender		
	Male	Female
Febrile	50.54	58.2
Respiratory	3.21	3.15
Infection	6.54	4.38
Injury	3.57	1.46
Other/missing	36.15	32.81

Table A.5: Health Provider Choice (RPM): Heterogeneity by gender and illness type

	(1)	(2)
distance	0.304672***	0.303995***
	(0.034)	(0.033)
distance (squared)	-0.004809***	-0.004803***
	(0.000)	(0.000)
Residual CF	0.629327***	0.626292***
	(0.044)	(0.042)
Residual CF (squared)	0.001839	0.001700***
	(0.002)	(0.000)
alternative: public	-5.4e+00***	-5.4e+00***
	(0.536)	(0.533)
alternative: private	-5.1e+00***	-5.1e+00***
	(0.532)	(0.529)
alternative: doctors	-4.3e+00***	-4.3e+00***
	(0.598)	(0.595)
num. doctors	0.105534***	0.115702***
	(0.040)	(0.041)
generator	0.609020***	0.608859***
	(0.067)	(0.064)
beds	-0.013711	-0.015179
	(0.012)	(0.010)
price X febrile illness	-2.2e+00***	-1.9e+00***
	(0.172)	(0.159)
price X respiratory illness	-0.716334***	-0.703497***
	(0.090)	(0.050)
price X infectious disease	-0.742494***	-0.723142***
	(0.118)	(0.046)
price X injury	-0.689956***	-0.683160***
	(0.069)	(0.104)
price X other types	-1.3e+00***	-1.2e+00***
	(0.154)	(0.102)
price X febrile X female		-0.438627***
		(0.140)
price X respiratory X female		-0.007809
		(0.024)
price X infectious X female		-0.083684
		(0.152)
price X injury X female		-0.010676
		(0.032)
price X other types X female		-0.149705***
		(0.052)
Standard deviations		
num. doctors	0.020809	0.004348
	(0.026)	(0.021)
generator2009	0.001056	0.003319
	(0.006)	(0.007)
beds	0.019622***	0.020346***
	(0.008)	(0.006)
price X febrile illness	1.4e+00***	1.3e+00***
	(0.135)	(0.117)
price X respiratory illness	0.014733	0.015738
	(0.023)	(0.030)
price X infectious disease	0.000355	0.001428
	(0.003)	(0.005)
price X injury	0.023921	0.024647
	(0.065)	(0.160)
price X other types	-0.545783***	0.577858***
	(0.126)	(0.062)
price X febrile X female		-0.680476***
		(0.079)
price X respiratory X female		0.003482
		(0.003)
price X infectious X female		-0.033716
		(0.107)
price X injury X female		-0.031084
		(0.028)
price X other types X female		-0.270614***
		(0.041)
N	39123	39123
MLL	-3824.8	-3814.7
LR test of q=10 restrictions (χ^2)		20.13
		0.0280

The table shows the Random Parameter Model estimates for the demand of health care allowing for heterogeneous responsiveness to price by illness type and by gender. Bootstrapped clustered standard errors are in parenthesis and are estimated using 500 replications. Variables with X indicate interactions terms between the lowercase variables. * p<0.10, ** p<0.05, *** p<0.01

Table A.6: Health Provider Choice (RPM): Heterogeneity by bargaining power, gender and age of husband/wife

	(1)	(2)
distance	0.326769***	0.326715***
	(0.040)	(0.043)
distance (squared)	-0.004950***	-0.004990***
	(0.001)	(0.001)
alternative: public	-6.4e+00***	-5.8e+00***
	(0.664)	(0.685)
alternative: private	-6.4e+00***	-5.6e+00***
	(0.647)	(0.677)
alternative: doctors	-5.3e+00***	-4.9e+00***
	(0.728)	(0.776)
residual CF	0.484432***	0.617736***
	(0.046)	(0.054)
residual CF (squared)	0.000125	-0.001572***
	(0.000)	(0.000)
num. doctors	-0.041237	0.070285*
	(0.034)	(0.041)
generator	0.573961***	0.840291***
	(0.062)	(0.080)
beds	-0.003421	-0.053165***
	(0.004)	(0.012)
price	-0.475436***	-1.2e+00***
	(0.050)	(0.169)
price X female	-0.081943	0.106466
	(0.050)	(0.157)
price X low bargaining status	-0.004998	-0.016844
	(0.013)	(0.036)
price X female X low bargaining status	-0.377887***	-0.261931***
	(0.146)	(0.077)
price X age of husband	0.000424	
	(0.000)	
price X age of husband X female	0.000855	
	(0.001)	
price X age of wife		0.006515**
		(0.003)
price X age of wife X female		-0.014132***
		(0.003)
Standard deviations		
num. doctors	0.004776	0.009720
	(0.006)	(0.017)
generator	0.004311	0.013689
	(0.008)	(0.016)
beds	0.004447	0.036988***
	(0.004)	(0.005)
price	0.001057	0.547915***
	(0.007)	(0.070)
price X low bargaining status	0.001406	0.031523***
	(0.013)	(0.009)
price X female	0.000837	0.664562***
	(0.003)	(0.095)
price X female X low bargaining status	0.325563***	0.566124***
	(0.094)	(0.076)
price X age of husband	0.000043	
	(0.000)	
price X age of husband X female	0.000075	
	(0.000)	
price X age of wife		0.000639*
		(0.000)
price X age of wife X female		0.010712***
		(0.001)
N	13639	13639
MLL	-1443.6	-1400.6

The table shows two robustness specifications of the Random Parameter Model estimates for the demand of health care allowing for heterogeneous responsiveness to price by gender and household bargaining status measured by the age difference between husband and the wife. They control for age of the husband (Column 1) and age of the wife (Column 2) to rule out that the effect of the bargaining power variable is driven by disproportionately older husbands or younger spouses. * p<0.10, ** p<0.05, *** p<0.01