Measurement Error in Discrete Health Facility Choice Models: an Example from Urban Senegal

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Acknowledgements: Funding for this work comes from the Bill & Melinda Gates Foundation (52037). This research was also supported by a Population Research Infrastructure Program (P2C HD050924) awarded to the Carolina Population Center at the University of North Carolina at Chapel Hill by the Eunice Kennedy Shriver National Institute of Child Health and Human Development. The contents of this paper are solely the responsibility of the authors and do not necessarily represent the official views of the funders. The authors would also like to thank Jennifer Winston, Veronica Escamilla, and Jeehoon Han for their assistance in the preparation of this manuscript.

Conflict of Interest Statement: The authors declare that they have no interest or relationship, financial or otherwise, that might be perceived as influencing our objectivity.

Summary: We use individual-level health facility choice data from urban Senegal to estimate consumer preferences for facility characteristics related to maternal health services. We find that consumers consider a large number of quality related facility characteristics, as well as travel costs, when making their health facility choice. In contrast to the typical assumption in the literature, our findings indicate that individuals frequently bypass the facility nearest their home. In light of this, we show that the mismeasured data used commonly in the literature produces biased preference estimates; most notably, the literature likely overestimates consumer distaste for travel.

Keywords: Measurement Error, Discrete Choice, Maternal Health, Senegal, Mixed Logit, Selection on Observables

JEL Classification: I12, I15, I18, J13, C35

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I. Introduction

Many developing countries have attempted to improve the health of their populations through government policies that enhance the quality and/or accessibility of healthcare (Yates, 2009). Given resource constraints, politicians and public health officials regularly evaluate competing policies by comparing projected costs and benefits. These projections require an understanding of how individuals evaluate the tradeoffs between the price, quality, and indirect costs (e.g., travel costs, wait times, etc.) faced in obtaining care. For example, consider a government that wishes to extend services to an underserved population and must decide between constructing a new health facility and improving an existing one(s). Evaluating these alternatives requires information on patient preferences for travel costs relative to preferences for facility quality and price sensitivity.

The choice models frequently employed in the economics literature are particularly well suited to extract such preference information from individual-level choice data (Train, 2009). However, the facility choice models that have been estimated in developing country settings have suffered from a common data limitation; namely, researchers have been unable to match individuals to the actual health facility that they visit. Most commonly, researchers utilize Demographic and Health Survey (DHS) data, which only reports the type of facility that an individual visits (e.g., public or private hospital, health center or dispensary; or traditional healer); therefore, researchers estimate choice models that (i) define the alternative set by the nearest facility of each type (Akin et al., 1986; Dor et al., 1987; Mwabu et al., 1993; Leonard et al., 2003; Mariko, 2003; Habtom and Ruys, 2007; Erlyana et al., 2011) or average facility of each type (Akin et al., 1995) and (ii) match individuals to the nearest facility of the type they report visiting.[1] This strategy may not be a major issue in rural areas with limited choice sets, but could be more important in urban areas. Regardless of the setting, estimates produced by these models vary considerably, offering no clear conclusions as to how individuals evaluate the tradeoffs faced in obtaining

[1] "Average facility of each type" implies that average facility characteristics (e.g., facility age) are measured across all facilities of a particular that type (e.g., public hospital) within some distance band. Other papers have used patient-reported characteristics from the visited facility to fit hedonic characteristic models, which are then used to impute characteristics at non-visited facilities (Gertler et al., 1987; Bolduc et al., 1996; Borah, 2006).

medical care. For example, most researchers have found that individuals are more likely to select nearby facilities with lower prices and higher quality (Gertler et al., 1987; Akin and Hutchinson, 1999; Leonard et al, 2003; Borah, 2006; Habtom, 2007), yet numerous papers find that individual choice is not affected by the distance they must travel for care (Akin et al., 1986; Mwabu et al., 1993; Mariko, 2003; Erlyana et al., 2011) or that in some cases, individuals actually prefer longer distances (Akin et al., 1995; Bolduc et al., 1996). There is also wide variation in the magnitude of estimated effects. For example, Erlyana et al. (2011) find that for a rural population of uninsured adults in Indonesia, the price elasticity of demand for both community health centers and private doctors is insignificantly different from zero; however, a similarly rural population of adults in Benin studied by Bolduc et al. (1996) has an estimated price elasticity of demand of -2.48 for community health centers and -4.27 for private doctors.

In conflict with the existing literature are several studies showing that individuals, particularly those in urban environments, frequently bypass nearby health facilities to obtain higher quality care (Akin and Hutchinson, 1999; Leonard et al, 2003). We confirm this finding in our own data as well. As such, both the choices and alternative sets assigned to individuals in much of the existing research do not represent the true choices made and alternative sets faced by the individuals being studied. These data deficiencies represent a form of measurement error that may bias existing estimates of consumer preferences for health facility characteristics. Ultimately, correcting this bias is important for health officials who utilize preference estimates to design policies that alter the price, quality, and/or indirect costs of both private and public health facilities.

In this paper, we utilize individual and health facility data that contain over 9,600 urban dwelling Senegalese women and 231 health facilities offering maternal health services. We use individual-level survey data to identify the facilities women visit for care, facility-level survey data to measure quality of care at each of the health facilities, and GPS coordinates to measure the distance each woman must travel to each facility. Together, this information allows us to estimate a health facility choice model that (i) matches women to the specific facility they visit and (ii) allows choices from the full set of alternatives. To our knowledge, no other work in the development economics literature can make this claim. Thus, the primary contribution of this paper is that it provides facility preference estimates in a developing country setting that are free of the bias caused by a common form of measurement error.

In our empirical analysis, we utilize a random utility framework to estimate a series of health-facility choice models, employing a selection-on-observables approach to control for the possible non-random self-selection of individuals into care. Our preferred parameter estimates are derived from a mixed logit (sometimes also referred to as a random-parameters logit) model, which relaxes the independence of irrelevant alternatives (IIA) assumption that is characteristic of the standard conditional logit model by allowing variation in the weight individuals place on facility characteristics when making decisions. Because we observe a complete census of facilities that offer maternal health services, we are able to mimic the literature by estimating an additional model that (i) restricts the individual's health facility alternative set to those nearest them that are of a particular type and (ii) matches the individual to a facility according to the type we observe them select. By comparing the two sets of estimates, we make an additional contribution, which is to quantify the bias in existing preference parameter estimates due to the measurement error that is common in the existing literature.

Our main findings indicate that patients prefer facilities that are nearby and facilities that are of high quality, such as facilities that offer a greater number of services, offer educational materials and conduct community outreach, and have modern amenities (e.g., electricity, piped water, telephones, and modern rooms). The preference for quality means that in many circumstances, patients are willing to bypass the closest facility for one of higher quality. We also find evidence to suggest that measurement error is a significant source of bias in the existing literature. Among the health facility characteristics that are under/over valued by the models estimated using data that is measured with error, the bias in preferences for distance is notable. Our findings suggest that, at least for urban Senegal, the matching procedure commonly used by researchers significantly limits the possibility that women travel long distances to obtain care, which leads to a systematic overestimate of the distaste for travel.

We highlight a potential consequence of the bias in preference parameter estimates by comparing how our preferred model and the measurement error model predict individual responses to two public policy actions; the first of which was actually implemented in 2014, after our data were collected – a new public facility was added in an underserved area of Dakar, Senegal – and the second of which is hypothetical, but can be viewed as having been a viable alternative to the observed action – providing electricity to facilities in Dakar without it. We find notable differences in the predictions produced by the two models, suggesting that the bias in preference parameter estimates caused by measurement error could have significant effects on public policy.

Our paper also contributes to a large literature on how individuals in *developed* countries evaluate the tradeoff between the price, quality, and indirect costs of obtaining medical care. While this literature does not grapple with the measurement error challenges discussed above, frequent use of administrative facility choice data creates the potential for endogenous sample selection – i.e., typically, a researcher only observes individuals who choose to visit a facility (e.g., Luft et al., 1990; Burns and Wholey, 1992; Hodgkin, 1996; Chernew et al., 1998; Mukamel et al., 2004; Dranove and Sfekas, 2008). In our survey data, we observe women that both visit and choose not to visit a facility, allowing us to model and ultimately test for endogenous selection of women into visiting a facility. We do not find evidence of endogenous selection, providing some support for the exogenous sample selection assumption made frequently in the developed country health facility choice literature.

In the following section, we detail the random utility model that guides our empirical specification and provide information on the statistical specification of the model. In Section III, we provide descriptive statistics for the individual and facility-level data used to estimate our model. We present estimation results, robustness checks, and policy simulations in Section IV. In Section V we summarize our findings and contributions to the health facility choice literature.

II. Model and Methods

We model the choice of health facility for maternal health services. The following random utility model, originally developed by McFadden (1974), serves as a baseline:

$$U_{ij} = X_{ij}\beta + Z_i\gamma_j + \epsilon_{ij} \tag{1}$$

where U_{ij} is the utility that individual $i = 1, 2, \ldots, N$ receives from facility $j = 1, 2, \ldots, J$. The X_{ij} represents a $1 \times L$ vector of choice-specific attributes such as the distance between individual i's place of residence and facility j. The Z_i represents a $1 \times K$ vector of individual-specific variables such as age and education. The baseline model assumes that the ϵ_{ij}'s follow a Type 1 Extreme Value (T1EV) distribution, are independent across alternatives, and have the same variance.

There are three problems with the baseline model. First, in order to allow individual-specific variables, Z_i, to impact choice probabilities directly in this specification we must estimate $(J - 1) \times K$ parameters, γ_j. In our model, $J = 231$, so the number of parameters that we would need to estimate to include even one main effect of an individual-specific variable is unfeasibly large. As such, we do not allow for Z_i to impact facility choices directly in our preferred model, though we do include interaction effects (between X_{ij} and Z_i) in some of the specifications discussed below.

Second, a nice feature of random utility models with T1EV errors is that they yield choice probabilities that have a closed form. However, a well-known critique of this distributional assumption is that the resulting probabilities display Independence of Irrelevant Alternatives (IIA), which imposes on the model strict substitution patterns between alternatives (Chipman, 1960; Debreu, 1960). In general, if there is any correlation between the unobserved preferences for alternatives (i.e., $Cov(\epsilon_{ij}, \epsilon_{ik}) \neq 0$), then these substitution patterns will be inappropriate. Our preferred model adopts an extension of the random utility model that is sometimes referred to as the mixed logit model (see Train 2009, Ch. 6). Specifically, we assume that preferences for facility attributes vary across the population such that $\beta_i \sim N(\beta, \Sigma)$ where β is an $L \times 1$ vector of means and Σ is an $L \times L$ covariance matrix. By allowing for random taste variation we implicitly allow for correlation between the model's error terms, which relaxes the IIA property and the strict substitution patterns characterizing the baseline model. The mixed logit specification also gives us a straightforward way to allow individual-level characteristics to impact choices in our model, while still allowing for preference heterogeneity. In several specifications, we allow the mean of the parameter distribution, β, to vary by an individual's income and education, which only requires the estimation of L additional parameters.

The third potential problem with the baseline model stems from the fact that we only observe facility choices for a non-randomly selected sub-sample of the population. Women in the survey data can choose not to visit a health facility, $S_i = 1$; to visit a health facility that we do not observe, $S_i = 2$; or to visit a health facility that we do observe, $S_i = 3$. We are only able to model the choice of a health facility if $S_i = 3$. Wooldridge (1999) shows that the parameters of the baseline model (i.e., Equation 1) can be consistently estimated via maximum likelihood using only the selected sample as long as S_i and ϵ_{ij} are uncorrelated (i.e., there are no unobserved determinants of facility choice that would lead an individual who visits a facility to choose a different facility from an observationally equivalent individual who does not visit a facility). This condition may not hold true in our setting, particularly because we cannot estimate the baseline model (Equation 1) due to the size of the alternative set. Instead, we estimate

$$U_{ij} = X_{ij}\beta_i + \omega_{ij} \tag{2}$$

where our error term is $\omega_{ij} = Z_i\gamma_j + \epsilon_{ij}$. Therefore, by excluding the main effects, $Z_i\gamma_j$, we increase the likelihood that selection into the sample, S_i, and the unobserved determinants of facility choice, ω_{ij}, are correlated (i.e., $E[\omega_{ij}|X_{ij}] \neq E[\omega_{ij}|X_{ij}, S_i = 3]$), which could bias parameter estimates in Equation (2).

We address this problem using a selection-on-observables approach described by Wooldridge (2002, 2007) and Imbens (2014). Assume that selection is influenced by an individual's characteristics, Z_i; the characteristics of health facilities that she is likely to visit conditional on visiting any facility, X_{ij} (where $j \in J^i$ and J^i is a set of such facilities); and some T1EV random component η_i. S_i can then be modeled using a random utility framework, where the probability of selecting into any of the three groups is

$$P(S_i = s|X_i, Z_i) = \frac{\exp\left(\delta_{1,s}f(X_i) + \delta_{2,s}Z_i\right)}{\sum_{s'=1}^{3}\exp\left(\delta_{1,s'}f(X_i) + \delta_{2,s'}Z_i\right)} \tag{3}$$

where $f(X_i)$ is a set of summary statistics characterizing the facilities in J^i (e.g., the average characteristics of facilities within a 1 km radius of individual i's home). The parameters of Equation 3 can be consistently estimated using maximum likelihood. We then weight the facility choice probabilities by the inverse of the predicted probability (IPW) that the individual visits a facility that we observe.

$$IPW = \frac{1}{\hat{P}(S_i = 3|X_i, Z_i)} \tag{4}$$

Further discussion on the tradeoffs associated with the weighted and unweighted estimators can be found in Section A of Cronin, Guilkey, and Speizer (2019), a Supporting Information Appendix. This section also discusses endogenous sample selection in the existing literature.

III. Data and Descriptive Statistics

Our empirical analysis focuses on urban areas in the West African country Senegal. Senegal is characterized by high fertility rates (5.1 children per woman in 2013; World Bank), high infant mortality rates (45 per 1,000 live births in 2012; Unicef), high maternal mortality rates (370 per 100,000 live births in 2008-2012; Unicef), and low rates of family planning use (21.2% of women in union ages 15-49 were using a modern method in 2015; DHS). As such, in recent years much attention has been paid to maternal and child health service quality and accessibility in both rural and urban areas of Senegal.

We use baseline individual and facility survey data from the Measurement, Learning & Evaluation (MLE) project collected as part of the evaluation of the Initiative Sénégalaise de Santé Urbaine (ISSU). The study included six urban sites: Dakar, Guédiawaye, Pikine, Mbao, Mbour, and Kaolack. A discussion of the sampling design and survey details can be found in Section B of Cronin et al. (2019).

III.a Choice Data

During the individual interview, women provided the name and address of the health facility that they visit "most frequently" for a number of health services. Responses were matched to facility-level information obtained in the facility survey. Our analysis focuses on the choice of a facility for maternal health services, which includes delivery, prenatal, and postpartum care. This choice data is summarized in Table 1. Of the 9,325 women in our sample, 7,034 had not visited a facility for maternal health services in the past 12 months. Among those visiting a facility, 1,830 report visiting a facility that was identified and surveyed by survey administrators.

These data are unique in that women can be matched to the specific facility that they visit for care, rather than the closest facility of a particular type. Table 1 shows how the "closest facility" strategy can lead to measurement error in facility matches, particularly in dense urban settings. Among women visiting a health facility for maternal health services, only 25.7% visit the facility nearest their home and 38.6% visit the nearest facility of a particular type, where types are defined as public hospital, public clinic (e.g., health center, health post, case de santé), private clinic (non-affiliated), and denominational/NGO clinic. Furthermore, the median (mean) individual bypasses 4 (17) facilities to get to the facility that she visits.

Table 1: Facility Choices for Maternal Health Services

Observations	9,325
No visit (*S*=1)	7,034
Visit unobserved facility (S=2)	461
Visit observed facility (S=3)	1,830
Among women visiting an observed facility	
% visiting facility nearest home	25.7
% visiting nearest facility of a particular type	38.6
Mean # facilities bypassed	17.0
Median # facilities bypassed	4.0

*Notes: Facility types are Public Hospital, Public Clinic, Private Clinic, Denominational or NGO clinic.

One reason that some women bypass nearby facilities could be heterogeneity in preferences for distance, for example, a woman may actually prefer to go to a facility farther away from her place of residence for the sake of anonymity. Our preferred model allows for this type of variation in preferences. Another potential explanation is that women bypass nearby, low-quality facilities for higher-quality facilities, and facilities that offer more services, but are further away; we present evidence of this below.

III.b Facility Quality

Table 2 summarizes the characteristics of the 231 health facilities that women may visit for maternal health services. Several facility characteristics require explanation. *Any IEC materials* indicate the presence of any of eight Information, Education, and Communication family planning (FP) tools (e.g., posters, brochures, demonstration models, etc.), which are visually verified by the survey administrator. In the facility survey, interviewees select the *number of services offered* from a list of 22 possible reproductive health services. Facilities are said to *provide community outreach* if they report having ever hosted health talks for the benefit of the community. Finally, the *distance* between each facility and a woman's home is measured, using ArcGIS software, as the straight-line distance between the centroid of the PSU where the woman lives and the facility location. PSUs, on average, include about 100-150 urban households, making this a fairly accurate representation of the location of a woman's home; however, there are other two reasons why this measure may not perfectly capture "travel costs" associated with obtaining care from a particular facility. First, straight-line distance does not consider road quality or transportation networks between the two points. This problem is common in the literature; however, our focus on urban environments, where roads exist and public transportation is widely available, likely minimizes any meaningful discrepancies. Second, our measure assumes that every facility visit starts and ends at the home. In reality, women may schedule visits in conjunction with other travel, such as work (34% of women in the data work), shopping, transporting children, etc; thus, facilities located along a woman's regular travel route may have lower travel costs, holding straight-line home-to-facility distance fixed. This problem is pervasive in the literature, as collecting data on routine travel is difficult.

In columns 2 and 3 of Table 2, we compare the average characteristics of both chosen and nearest facilities.[2] The differences are stark; virtually every characteristic associated with quality is higher for the chosen facility than the nearest facility. Most notably the average chosen facility is open more days and

[2] In our choice models, we distinguish between non-identified and non-participating facilities. Surveyors failed to identify 38 facilities on the master list. We do not observe any information about these facilities in the data; thus, we control for potentially endogenous selection into these facilities in the choice model in the first stage (see Section 2 above). There are 26 facilities that surveyors were able to identify, but that refuse to participate in the survey. Among these, we observe distance and facility type (i.e., *public hospital, public clinic, private clinic, denominational/NGO clinic*); thus, these facilities enter the choice model as alternatives with all unobserved characteristics coded as 0. The control variable *participate in survey* distinguishes preferences that are unique to these facilities. For robustness, we also estimated our model treating non-participating facilities as non-identified. These results are presented in column 1 of Table A3 in Cronin, Guilkey, and Speizer (2019), a Supporting Information Appendix, and are virtually identical to our main findings.

hours, has a larger staff, offers more services, is more likely to conduct community outreach programs, and is more likely to be equipped with modern amenities than the nearest facility.

Table 2: Health Facility Characteristics

	(1) All Facilities	(2) Chosen Facility	(3) Nearest Facility
distance (km)	62.93	4.10	0.46
public hospital	0.03	0.11	0.00
public clinic	0.71	0.77	0.80
private clinic	0.19	0.07	0.09
denominational/NGO clinic	0.07	0.05	0.11
age	25.58	27.78	22.28
open 7 days a week	0.57	0.73	0.57
hours a day	16.64	18.91	15.65
any IEC materials	0.69	0.83	0.78
# doctors	2.23	3.72	0.78
# nurses	3.71	5.48	2.47
# midwives	2.85	4.79	2.14
any health social worker	0.21	0.33	0.14
# services offered	16.01	18.26	16.52
provides community outreach	0.58	0.77	0.71
has electricity	0.96	0.98	0.96
has telephone	0.81	0.80	0.73
has private rooms	0.87	0.96	0.89
participated in survey	0.89	0.97	0.96
observations	231	1,830	1,830

*Notes: Column 1 contains average characteristics for facilities in the sample. Distance to any facility varies by woman, so the average distance is calculated using all 9325*231 observations. Moreover, while distance and facility type are observable for all 231 health facilities, the remaining variables are only observable for the 205 facilities participating in the survey. Column 2 contains average faciliy characteristics for the 1,830 facilities selected by individuals. Column 3 contains average faciliy characteristics for the 1,830 facilities located nearest the homes of women visiting a facility for maternatl health services. Facilities in both columns 2 and 3 are not mutually exclusive within or across categories.

IV. Results

In this section, we present estimates from a series of econometric models. Our preferred estimates are taken from an unweighted, mixed logit model (Equation 2 above) that utilizes choice data that is not characterized by the measurement error common in the literature. In Section IV.a, we conduct formal hypothesis tests showing that (i) the weighting strategy discussed in Section II has no significant impact on parameter estimates and (ii) allowing for preference heterogeneity significantly improves model fit. In Section IV.b, we discuss preference parameter estimates from our preferred model. In Section IV.c, we discuss several robustness tests and alternative model specifications. In Section IV.d, we impose on our data the measurement error that is commonly observed in the literature and show that this error creates bias in preference parameter estimates. In Section IV.e, we conduct two policy experiments that highlight how the bias created by this measurement error can impact policy analysis.

IV.a Testing for Endogenous Selection and Independence of Irrelevant Alternatives

We begin by estimating four choice models: unweighted conditional logit, unweighted mixed logit, weighted conditional logit, and weighted mixed logit. Results are presented in Table A1 of Cronin et al. (2019). Recall that the two weighted models require the estimation of a (first-stage) selection equation. Selection is modeled as a function of demographic characteristics (e.g., age, income, education, religion, etc.), survey responses thought to explain the likelihood that a woman would seek maternal health services (e.g., currently pregnant, gave birth within past 2.5 years, number of children, etc.), average facility characteristics within a one-kilometer radius of the woman's home, and a large set of interactions. The results of this first-stage, and a list of specific controls used, can be found in Table A2 of Cronin et al. (2019). For the two mixed logit models, we restrict the parameter covariance matrix, Σ, to be diagonal, allowing preference parameters to be random but uncorrelated.[3]

In general, identifying multinomial choice models requires that the variance of the error term (ω_{ij} from Equation 2) be normalized by the econometrician. Throughout, we will assume that ω_{ij} is distributed T1EV, which naturally imposes the assumption that $V(\omega_{ij}) = \pi^2/6$. Given this assumption, estimated preference parameters are interpreted as $\hat{\beta} = (\beta/\sigma) * \sqrt(\pi^2/6)$, where σ, the true variance of ω_{ij}, is unknown. For this reason, it is often said that these models are identified *up to scale*. See Train

[3] Given our assumptions, it is straightforward to construct the likelihood function for this problem (e.g., see Train, 2009, Ch.6). We use Stata's *mixlogit* package, which uses simulated maximum likelihood. Results presented here use 50 Halton draws, which Bhat (2001) shows provide better accuracy with fewer draws and lower computational time than a pseudo-random method. Our main mixed logit model (i.e., Table 3, column 2) has also been estimated using 400 Halton draws. These results can be found in Appendix Table A4. Parameter sign and significance is very similar to the 50 draw findings, though magnitudes vary slightly. We have chosen to present the 50 draw results because estimating the model with 400 draws is computationally expensive, preventing bootstrapping, which is required for (i) calculating standard errors for parameter ratios and (ii) the hypothesis testing that follows.

(2009, Section 2.5.2) for more details. A consequence of this feature of multinomial choice models is that estimated preference parameters are not comparable across different specifications of the same model, if the specification difference could lead to a difference in model variance. As a result, throughout the paper (Table A1 included), we present ratios of preference parameters for facility attributes to distance. By dividing one preference parameter by another, we produce a set of estimates that are independent of model variance and are, thus, comparable across models. We use the distance parameter as a base because (i) it is highly significant in all models and (ii) produces parameter ratios that are easily interpreted as a consumer's willingness to travel for the facility attribute. We report standard errors that are based on 500 bootstrap replications where we sample with replacement from the set of respondents, estimate the model's parameters, and then calculate ratios relative to the estimated distance coefficient. This allows us to calculate the standard errors for each estimator and also joint covariance matrices for pairs of estimators that can be used in the Wald tests that we report.

We first test for endogenous selection into visiting any facility. As explained in Section II, estimates from the unweighted model are consistent only if selection is ignorable conditional on facility attributes, while consistency of the weighted model requires a weaker condition – that selection is ignorable conditional on facility attributes and other controls. We test the null hypothesis that the ratios of weighted and unweighted coefficient estimates are the same (i.e., a test of endogenous selection) using 500 bootstrap samples to construct an estimate for the joint covariance matrix of the sets of ratios. For the conditional (mixed) logit model, the resulting test statistic is 7.96 (6.03), which under the null hypothesis is chi squared with 17 degrees of freedom. As such, we fail to reject the null hypothesis that the estimated preference ratios taken from the models are jointly equal, meaning endogenous selection into treatment does *not* seem to bias our parameter estimates.[4] Our remaining results focus on unweighted estimators.

[4] Preference estimates for several facility attributes are insignificant in both models (e.g., hours a day, # of doctors, etc.), which reduces the power of the global test. Moreover, some preference estimates clearly vary between the two models (e.g., open 7 days a week). That said, it is interesting that coefficients are more precisely measured in the conditional logit model; however, we still fail to reject the null. In addition, there are almost no sign reversals for either the conditional and mixed logit models in the weighted versus unweighted results.

Next, we test whether the IIA assumption, which is imposed by the conditional logit (CL) model but not the mixed logit (ML) model, is appropriate. In Section 4 of McFadden and Train (2000), the authors note that because the ML model relies on an assumed parameter distribution, the ideal specification test of whether mixing is necessary would be based only on the CL model. The authors propose a test which follows these steps: (i) estimate a baseline CL model; (ii) construct the following artificial variables,

$$w_{ij} = \frac{1}{2}\left(X_{ij} - \tilde{X}_{iJ}\right)^2 \text{ with } \tilde{X}_{iJ} = \sum_{k \in J} X_{ik}\hat{P}_{ik} \tag{5}$$

where $\hat{P}_{ik}$ is the predicted probability that individual i selects alternative k, using the preference parameters from the baseline CL model; (iii) re-estimate the CL model including the artificial variables, w_{ij}; and (iv) conduct a likelihood ratio test of the null hypothesis that the artificial variables w_{ij} should be omitted from the CL model. We perform this test, which is asymptotically equivalent to a Lagrange multiplier test of the null of no mixing against the alternative of mixing, and reject the null hypothesis at the 0.001 level of significance. We also conducted (i) a Wald test using the bootstrap procedure described above, which tests the null hypothesis that the mean of the ML model parameters are equal to the non-random CL model parameters and (ii) the McFadden and Train (2000) test as well as a Wald test on the weighted models; we strongly reject the null hypothesis that the models are the same in each of these tests. As a result of these tests, the unweighted ML model is our preferred model.

IV.b Preference Parameter Estimates from our Preferred Model

Preference parameter estimates from the unweighted ML model are found in column 1 of Table 3; ratios of (mean) preference estimates for facility attributes to distance are presented in column 2. The ratios reported in panel A can be interpreted as the distance, in kilometers, that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Thus, for a given attribute preference level, a smaller ratio reflects a larger distaste for travel. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Our estimates suggest that women prefer high quality health facilities for maternal health services. Preferences for the following facility characteristics are positive and significantly different from zero at the population mean: facility age, open every day of the week, number of doctors, any health social worker, number of services offered, any IEC materials, any programs that share health information with the community, electricity, a telephone, and private rooms. Compared to public hospitals, women have significant, positive preferences for public clinics and denominational/NGO clinics and negative preferences for private clinics. It is likely that these facility type preferences largely capture preferences for prices, as well as unobserved quality characteristics, as public hospitals tend to be more expensive than other public clinics, but much less expensive than private facilities. We discuss the role of prices in more detail in the following section.

The mean preference for distance is negative and significantly different from zero. To place our estimate in the literature, we calculate a distance elasticity of demand using a method that is similar to Luft et al. (1990). First, we randomly select a facility for each individual. Second, we predict the probability of selecting this facility assuming that the distance that one must travel is equal to the average travel distance observed in the data (i.e., 0.41 km). For this prediction, we integrate over the estimated parameter covariance matrix using the Stata package *mixlpred* with 500 draws. Third, we predict the probability of selecting this facility assuming that the distance traveled is 10% longer (shorter) and calculate the elasticity. We find that a 10% increase (decrease) in distance decreases (increases) the probability of selecting that facility by about 21% (30%). These estimates are near those reported by Luft et al. (1990) – a 12-14% increase in hospital admissions given a 10% decrease in distance. That said, Luft et al.'s estimates reflect the preferences of hospital patients in San Francisco, meaning (among other possibilities) the difference in transportation networks between San Francisco and urban Senegal could explain the discrepancy. From the developing country literature, our elasticity estimates are similar in magnitude to those reported by Dor et al. (1987) for low-income Côte d'Ivorians traveling over an hour for care; elasticities between -0.87 and -2.26. Our estimates are much larger than those of Erylana et al. (2011), who study a similarly urban population in Indonesia. That said, estimates from this literature are biased by measurement error, which likely explains some of the differences across studies.

Table 3: Preferred Mixed Logit Model, Complete Data

Covariates	(1) Unweighted, Mixed Logit Params	SE	(2) Unweighted, Mixed Logit Ratio	SE
Panel A: Mean Coefficients				
distance (km)	-1.032	0.058	-1.000	
public clinic	0.235	0.114	0.227	0.129
private clinic	-0.957	0.281	-0.927	0.169
denominational/NGO clinic	0.567	0.181	0.550	0.174
age	0.010	0.001	0.010	0.001
open 7 days a week	0.456	0.106	0.442	0.108
hours a day	-0.001	0.006	-0.001	0.006
# doctors	0.033	0.006	0.032	0.012
# nurses	0.000	0.007	0.000	0.007
# midwives	0.019	0.012	0.019	0.011
any health social worker	0.654	0.072	0.633	0.073
# services offered	0.075	0.016	0.073	0.018
any IEC materials	0.477	0.079	0.462	0.082
provides community outreach	0.262	0.072	0.254	0.076
has electricity	1.077	0.178	1.043	0.179
has telephone	0.649	0.074	0.629	0.085
has private rooms	1.020	0.165	0.988	0.164
participated in survey	-4.597	0.399	-4.454	0.452
Panel B: Std. Dev. of Coef.				
distance (km)	0.557	0.037	0.540	0.034
public clinic	0.142	0.323	0.138	0.293
private clinic	1.149	0.317	1.113	0.298
denominational/NGO clinic	0.282	0.319	0.274	0.175
age	0.002	0.001	0.002	0.001
open 7 days a week	0.006	0.134	0.006	0.084
hours a day	0.010	0.008	0.009	0.004
# doctors	0.006	0.019	0.005	0.015
# nurses	0.014	0.010	0.014	0.009
# midwives	0.009	0.006	0.009	0.004
any health social worker	0.086	0.124	0.083	0.065
# services offered	0.003	0.011	0.003	0.007
any IEC materials	0.001	0.201	0.001	0.092
provides community outreach	0.043	0.203	0.042	0.095
has electricity	0.039	0.149	0.038	0.122
has telephone	0.144	0.290	0.139	0.169
has private rooms	0.221	0.273	0.214	0.198
participated in survey	0.117	0.164	0.113	0.110
Number of Individuals	1,830			
Number of Obervations	422,730			
LLF	-5,815.555			

*Notes: The ML model is estimated using the Stata package *mixlogit*, which uses maximum simulated likelihood, with 50 Halton draws. The reference facility type is a public hospital. Parameter estimates are reported in column 1. The ratios reported in column (2), which are independent of scale, are formed by dividing the mean (and standard deviation) of the preference parameters by the negative of the mean preference for distance. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Ratio standard errors are calculated via bootstrap procedure described in section IV.a.

The first row, first column in Panel B of Table 3 reveals wide variance in preferences for distance across the population. That said, only 3.2% of the population is predicted to have *positive* preferences for distance, which seems appropriate. The panel also reveals wide variance in preferences for private clinics. For the average individual, private clinics are the least desired facility type; however, 20.3% of the population prefers private clinics to public hospitals and 9.2% prefer private clinics to all care types. For all other preference parameter distributions, the standard deviation is not significantly different from zero.

IV.c Robustness and Alternative Specifications

In this section, we briefly describe several robustness tests and alternative specifications that were estimated; however, many details are reserved for a Supporting Information Appendix (see Cronin et al., 2019). As mentioned in footnotes 2 and 3, respectively, our preferred model is robust to (i) dropping non-participating facilities and (ii) increasing the number of Halton draws used in the maximum simulated likelihood procedure. Another potential concern is our assumption that each woman has access to the same health facility alternative set, despite the fact that women and facilities are drawn from three different regions of Senegal – Dakar, Mbour, and Kaolack; Dakar is roughly 69 km from Mbour and 178 km from Kaolack, while Mbour is 109 km from Kaolack. The concern is that our model may mistake a distaste for travel, because women rarely travel to these far-off facilities, with lack of knowledge (see Section C of Cronin et al. (2019) for more details). As such, we perform two robustness tests. In column 2 of Table A3 in Cronin et al. (2019), we estimate our preferred model while dropping the 29 women leaving their home region for maternal health services. In column 3 of the same table, we estimate the same model while also constraining each woman's alternative set to the facilities in her home region. A Wald test, conducted using the same bootstrap procedure described in Section IV.a, reveals no significant difference between these estimates and those using the full sample.

One drawback of our data is that they do not contain information on the price of delivery or user fees charged for prenatal and postnatal care. As a result, we argue that the preference parameters on facility type indicators *public clinic*, *private clinic*, and *denominational/NGO clinic* should be interpreted as capturing price sensitivity, as well as preferences for unobserved quality. In Table A5 of Cronin et al. (2019), we estimate two models that highlight the role that unobserved prices have on our estimates. In column 1, we estimated a model that replaces facility type indicators with a price variable that is generated using external data on the average price charged for delivery at each facility type, (see Section D of Cronin et al. (2019) for more details). Model estimates suggest that the demand for maternal health services is inversely related to prices. In column 2, we estimate a model that includes an expanded set of facility type indicators, but no control for prices. These estimates show (i) women have similar preferences for similarly priced facilities and (ii) preference for facility types is *almost* perfectly negatively correlated with average delivery prices at the facility – i.e., women have strong preferences for the cheapest facilities (public health center) and weak preferences for the most expensive (private clinics). Denominational and NGO facilities are an exception. These facilities are moderately priced, but women have strong preferences for them, likely reflecting high unobserved quality. These estimates, along with average price information, rationalize our grouping of facilities into the types used in our main specification.

Our ML specification confirms that preferences for travel and facility quality vary across the population. We estimated two additional specifications to understand whether this preference variation can be explained by observable characteristics. In Cronin et al. (2019), column 1 of Table A6 (discussion in Section E), we allow the mean of the preference distribution for each facility characteristic to vary by household income – above or below the second quintile; in column 2, we allow for variation by whether the woman has any formal education - 40 percent do not. We find that those with less income are more averse to travel. Both low income and low education groups have weaker preferences for private facilities, suggesting both groups are more price sensitive. Note also that when preferences are allowed to vary by household income, the estimated variance in preferences for private clinics decreases, suggesting that much of the original variance in this parameter distribution was due to income. Both disadvantaged groups also have weaker preferences for facilities with longer hours, possibly reflecting lower rates of employment, and stronger preferences for facilities offering more services.

IV.d Facility Choices with Measurement Error

Existing research on the determinants of health facility choice in developing countries is hampered by data limitations. Many researchers analyze Demographic and Health Survey (DHS) data, which rarely report the exact facilities that a woman visits for care; rather, these data report the type of facilities that she visits (e.g., public or private hospital, health center or dispensary; or traditional healer). A popular solution to this problem is to (i) define a woman's facility alternative set by the facilities of each type that are nearest her home and (ii) match her to the nearest reported type (Akin et al. 1986; Dor et al. 1987; Mwabu et al., 1993; Leonard et al., 2003; Mariko, 2003; Habtom and Ruys, 2007; Erlyana et al. 2011). This strategy creates measurement error in both the alternative set and choice outcome, potentially biasing preference parameters in a direction that is ex-ante unknown. The strategy essentially eliminates the possibility that a woman travels a long distance to receive care, which may lead to an overestimation of preferences against travel; however, the strategy also removes far-off unselected facilities from the alternative set, which could lead to an underestimation of preferences against travel.[5] Moreover, the strategy reduces variability in the distance variable, which (by analogy to the linear model) leads to larger standard errors on the distance preference parameter, making it more difficult to obtain significant effects.

Not only are our individual-facility matched data free of this measurement error, but our data can be manipulated to reflect the measurement error that other researchers face in order to determine the resulting bias in preference parameter estimates. To create the measurement error typically observed in the literature, we limit our sample in several ways. First, we define four facility types: public hospitals, public clinics, private clinics, and denominational/NGO clinics. Second, we limit every woman's alternative set to the 4 facilities (one of each type) that are nearest her home. Third, we match each woman to the nearest facility matching the *type* of facility that she actually visits, rather than the actual facility, which may no longer be in her alternative set. Finally, we re-estimate the choice models and

[5] While much of the existing literature has studied urban, or a mixture of urban and rural, dwellers (e.g., Akin et al., 1995; Mariko, 2003; Habtom and Ruys, 2007; Erlyana et al., 2011), some researchers have studied purely rural environments, where it is likely that facility quality is less heterogeneous and travel is more costly. Women may be less likely to bypass facilities in these settings, thus reducing the measurement error described above.

compare the results to the models estimated using data without measurement error.

The measurement error results, as well as corresponding results using the complete data, can be found in Table 4. Columns 1 and 2 report parameter estimate ratios from an unweighted CL model using the mismeasured and complete data, respectively. Most of the literature estimates this model; however, as we showed in Section IV.a, we reject the CL model in favor of the ML model. Columns 3 and 4 of Table 4 report parameter estimate ratios from ML specifications using mismeasured and complete data, respectively. Using our preferred set of controls and mismeasured data, the ML model likelihood function fails to converge when the data are measured with error, so we report a slightly different specification here, where facility type indicators are fixed rather than random across the population. In Table A7 of Cronin et al. (2019), we present an alternative specification where facility type indicators are replaced with the price variable described in Section IV.c.

We formally test the competing models for significant differences in the estimated preference parameter ratios using a Wald test and the bootstrapping strategy discussed in Section IV.a. For the fixed facility types specification (i.e., Table 4) the test statistic is 83.86 with 17 degrees of freedom; for the price specification (i.e., Table A7 of Cronin et al., 2019) the test statistic is 65.47 with 15 degrees of freedom. Thus, in both cases, we strongly reject the null hypothesis that the vector of ratios is the same, making it clear that the model with measurement error yields misleading results.

The potential consequences of not accounting for this measurement error are understood by simply comparing the sign and significance of preference parameter ratios in the competing models. These comparisons reveal a number of differences. For example, using the fixed facility type specification (Table 4, columns 3 and 4), there are nine estimated parameter ratios that are significantly different from zero at a 5 percent level when the model is estimated with complete data, but not when estimated with mismeasured data. Moreover, preferences for denominational/NGO clinics, facilities open 7 days a week, and number of midwives are found to be positive using the complete data, but negative using the measurement error data. Similar differences exist using the price specification (Table A7 of Cronin et al., 2019).

Table 4: Choice Model Estimates - Complete vs. Mismeasured Data

Covariates	(1) Cond. Logit, Mismeasured Data Ratio	SE	(2) Cond. Logit, Complete Data Ratio	SE	(3) Mixed Logit, Mismeasured Data Ratio	SE	(4) Mixed Logit, Complete Data Ratio	SE
Panel A: Mean Coefficients								
distance (km)	-1.000		-1.000		-1.000		-1.000	
public clinic	5.850	4.057	1.459	0.593	2.134	0.966	0.143	0.114
private clinic	-0.843	0.907	-4.648	1.532	-0.565	0.498	-0.509	0.128
denominational/NGO clinic	-1.337	0.942	3.631	1.100	-0.993	0.477	0.497	0.164
age	0.002	0.011	0.056	0.013	0.004	0.006	0.010	0.002
open 7 days a week	-0.095	0.680	2.251	0.752	-0.037	0.327	0.435	0.108
hours a day	-0.026	0.040	0.015	0.041	-0.014	0.020	0.000	0.006
# doctors	0.026	0.025	0.071	0.029	0.018	0.023	0.011	0.012
# nurses	-0.006	0.039	-0.018	0.029	-0.009	0.020	-0.005	0.007
# midwives	0.013	0.070	0.255	0.085	-0.010	0.034	0.025	0.012
any health social worker	0.929	0.720	1.700	0.385	0.520	0.325	0.659	0.074
# services offered	0.070	0.084	0.416	0.130	0.033	0.041	0.075	0.018
any IEC materials	0.103	0.639	1.058	0.463	0.030	0.307	0.487	0.083
provides community outreach	0.926	0.575	2.230	0.768	0.478	0.213	0.261	0.076
has electricity	2.311	1.717	5.582	1.646	0.836	0.479	1.061	0.182
has telephone	0.879	0.539	3.211	0.727	0.482	0.239	0.658	0.087
has private rooms	-0.149	0.826	5.099	1.318	0.180	0.329	0.986	0.175
participated in survey	-2.727	1.900	-22.026	4.843	-1.427	0.790	-4.472	0.472
Panel B: Std. Dev. of Coef.								
distance (km)					0.501	0.068	0.601	0.034
public clinic **					0.000		0.000	
private clinic **					0.000		0.000	
denominational/NGO clinic **					0.000		0.000	
age					0.018	0.014	0.002	0.001
open 7 days a week					1.252	0.499	0.171	0.074
hours a day					0.002	0.029	0.010	0.004
# doctors					0.012	0.027	0.036	0.015
# nurses					0.025	0.023	0.026	0.009
# midwives					0.032	0.019	0.013	0.004
any health social worker					0.936	0.516	0.046	0.068
# services offered					0.042	0.023	0.020	0.007
any IEC materials					0.169	0.253	0.123	0.094
provides community outreach					0.065	0.231	0.297	0.084
has electricity					0.139	0.202	0.045	0.102
has telephone					0.362	0.424	0.331	0.186
has private rooms					0.168	0.334	0.212	0.212
participated in survey					0.032	0.056	0.108	0.099
Number of Individuals	1,830		1,830		1,830		1,830	
Number of Obervations	7,320		422,730		7,320		422,730	
LLF	-1,344.62		-6,921.388		-1,321.83		-5,801.75	

** Not estimated.

Notes: The following steps are used to generate measurement error in the data: (i) define four facility types: public hospitals, public clinics, private clinics, and denominational/NGO clinics; (ii) limit every woman's alternative set to the 4 facilities (one of each type) that are nearest her home; (iii) match each woman to the alternative matching the type of facility that she actually visits. The Complete Data includes all facilities in each individual's alternative set and matches individuals to the facility that they actually visit. Conditional and mixed logit models are estimated using Stata packages *clogit* and *mixlogit*, respectively. In both models, the reference facility type is a public hospital. The mixed logit models are estimated via maximum simulated likelihood, using 50 Halton draws. Ratios of parameters, which are independent of scale and thus comparable across models, are reported. These ratios are formed by dividing the mean (and standard deviation) of preferences by the negative of the mean preference for distance. Ratios in panel A can be interpreted as the distance that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Ratio standard errors are calculated via bootstrap proceedure described in section IV.a.

In an effort to say something more general about this type of measurement error, we have estimated an auxiliary model – a mixed logit choice model that features distance and any health social worker as the lone facility characteristics – using several combinations of mismeasured choice data. Recall, the empirical strategy used by many researchers generates two types of measurement error: (i) alternative sets are defined in a way that excludes far off facilities and (ii) individuals are matched to facilities that are, on average, closer than the facilities they actually visit. The first type of measurement error should lead to an underestimate of preferences against travel, which we show by estimating a model that imposes the first type of measurement error, but not the second. In Cronin et al. (2019), column 2 of Table A8, we present estimates from a model that defines the alternative set using the nearest facility of each type, plus the (true) visited facility, and matches individuals to their visited facility. In column 1, we report results using the complete data for comparison. As each model is only identified up to scale, preferences against travel can be compared across these specifications by comparing the ratio of the parameters. Preferences against travel are found to be over 25 times smaller when the alternative set is constrained. In column 3, we report estimates from a model that defines the alternative set using the nearest five facilities of each type, plus the visited facility, and matches individuals to their visited facility; clearly, the bias is reduced by moving closer to the true alternative set.

Next, we show that the second type of measurement error (i.e., matching individuals to facilities that are systematically closer to their homes than the true facilities) leads to the opposite effect, or an overestimate of preference against travel. In column 4, we report estimates from a model that defines the alternative set correctly, but matches individuals to the nearest facility of the type that they visit. Preferences against travel are found to be roughly eight times larger than when the correct match is made. We then show that this finding results from matching individuals to facilities that are systematically too close. In column 5, we report estimates from a model that defines the alternative set correctly, but matches individuals randomly to one of the three nearest facilities of the type that they visit; the bias in preferences against travel is reduced.

In the final column of Table A8, we replicate the literature, meaning we define the alternative set using the nearest facility of each type and match individuals to the nearest facility of the type that they visit. As these two types of measurement error have off-setting effects, preference estimates are biased, but less than the results presented in columns 2 and 4. Using our particular data, the bias caused by matching individuals to the wrong facility is stronger than the bias caused by an inaccurate alternative set; however, this conclusion cannot be reached generally.

To understand whether this type of measurement error has a net positive or negative impact on consumer preferences for travel, we compare the overall magnitude of willingness to travel measures, across models, for a select set of facility attributes. Our results are presented in Table 5. Column 1 (2) contains ratios of the ratios presented in columns 1 (3) and 2 (4) in from Table 4; thus, table elements measure the extent to which measurement error leads to the over/under valuing of distance relative to quality. For example, the first element in column 1 suggests that measurement error in the choice variable causes the CL model to overstate distaste for travel relative to preferences for any health social worker by 54.6 percent. To ensure that only statistically relevant measures of travel preference are considered, we only calculate this metric for the five facility attributes with preference parameters having p-values under 0.30 across all four relevant models.

For both the CL and ML models, measurement error in the choice variable causes the model to *overstate* a woman's distaste for travel, relative to her preference for quality. The bias is larger in the CL model. Averaging over the elements in column 1 (2), the CL (ML) model with measurement error suggest that in order to visit a facility with greater quality, women would only travel an additional 35.4 (91.6) percent of what they are truly willing to travel. Furthermore, while not shown, one could also form ratios of the ratios presented in columns 1 and 3 of Table 4, as well as in column 2 and 4. This exercise would clearly show that the CL model consistently produces larger quality-to-distance ratios than the ML model, both with and without measurement error. In other words, the CL model *understates* a woman's distaste for travel, relative to her preference for quality.

A final consideration of our analysis is the exemption of individual-level controls. While the existing literature commonly uses mismeasured choice data, the resulting alternative set is small, allowing individual-level controls to impact choice probabilities. A consequence of using complete choice data is that the alternative set is large, preventing the inclusion of individual-level controls. In Table A9 of Cronin et al. (2019), we present estimates from a multinomial choice model that uses aggregate (mismeasured) data and allows individual-level controls to impact the probability of selecting a facility of a particular type. Comparing the resulting parameter ratios to those found in Table 4, it is clear that the preference estimates most closely match those from the conditional logit model, estimated with mismeasured data and no individual-level controls (Table 4, column 1). Results from both the conditional (Table 4, column 2) and mixed (Table 4, column 4) logit models estimated with completed data differ substantially, suggesting that using mismeasured data *with* individual-level controls is no substitute for using complete choice data.

Table 5: Willingness to Travel for One Additional Unit of Quality

	(1) CL - ME ratio / Complete ratio	(2) ML - ME ratio / Complete ratio
Maternal Health		
any health social worker	0.546	0.789
	(0.513)	(0.443)
# services offered	0.169	0.438
	(.279)	(0.514)
provides community outreach	0.415	1.835
	(0.318)	(0.564)
has electricity	0.414	0.788
	(.465)	(0.384)
has telephone	0.274	0.733
	(.224)	(0.319)
Mean	0.364	0.916

*Notes: Table elements found in column 1 (2) form a ratio of the ratios presented in columns 1 (3) and 2 (4) in Table 4. Table elements measure the extent to which measurement error leads to the over/under valuing of distance relative to quality. For example, the first element in column 1 suggests that measurement error in the choice variable causes the CL model to overstate distaste for travel relative to preferences for any health social worker by 54.6 percent. The mean of these figures is calculated in the last row. Standard errors are reported in parenthesis. Note that only a subset of attributes are considered in this table. Attributes were chosen based on statistical significance of preference parameters across the four relevant models; all have p-values under 0.30.

IV.e Policy Experiments

In the previous section, we showed that the measurement error frequently found in the literature leads to an overestimate of a woman's distaste for travel, relative to preferences for facility quality. In this section, we conduct two policy related experiments using the parameter estimates from both the CL and ML models, estimated with and without measurement error, in an effort to highlight how the bias created by measurement error could impact policy conclusions. The first policy action that we examine took place in 2014 in Dakar, Senegal after our data was collected – a new public facility was added in northeastern Dakar. The new facility, which is marked by a star in Figure 1, is located in an area that was previously underserved. Data on this facility was collected in the third round of our survey data, which was conducted in 2015; thus, facility characteristics are perfectly observable. The facility is a public clinic, offers 19 of the 22 possible services, has a small staff of one nurse and one midwife, and has all modern amenities. Using all four previously referenced models, we simulate how many women will visit this new facility. Given that (i) our results from Section IV.d suggest that the measurement error models over-emphasize patient distaste for travel relative to preferences for quality and (ii) the new facility reduces the distance that some women must travel for care, we hypothesize that a model estimated with mismeasured data will predict that *more* women will visit the new facility than a model estimated with complete data.

The second policy is hypothetical – we consider providing electricity to the 6 participating health facilities in Dakar (5 public and 1 private) that report not having electricity at the time of the survey.[6] As public health officials are generally resource constrained, this hypothetical policy (i.e., improving the quality of existing health facilities) can be thought of as a realistic alternative to the first policy (i.e., adding a new facility), which was actually implemented. Figure 1 shows that the facilities without

[6] Note that several other hypothetical policy changes would ensure large differences between the models estimated with and without measurement error. For example, preferences for being open 7 days a week are negative in all measurement error models and positive in all non-measurement error models; as such, a policy mandating daily operations would clearly produce dramatically different policy predictions. We chose a policy experiment centered on adding electricity because (i) all models suggest that the population places a high value on facilities having electricity and (ii) this strikes us as a reasonable policy for the local government to consider.

electricity (marked by red triangles) are spread across Dakar. We again use all four models to predict how acquiring electricity affects the use of these facilities. Given that (i) our results from Section IV.d suggest that the measurement error models over-emphasize patient distaste for travel relative to preferences for quality and (ii) the policy improves facility quality for some facilities, but does not reduce the distance that any women must travel for care, we hypothesize that the model estimated with mismeasured data will predict a smaller increase in use among improved facilities than the model estimated with complete data.

The experimental choices are simulated for the 946 individuals living in Dakar that select a facility in our data. For the CL model, we take 500 simulation draws from a T1EV distribution for each individual-facility pair. The facility generating the most indirect utility determines an individual's choice. The procedure for the ML model is the same, though each simulation round also involves a draw from the parameter covariance matrix. Standard errors are calculated conditional on estimated parameters.

Policy experiment results are reported in Table 6. We find support for both of our hypotheses. For the first experiment, our preferred ML model predicts that an average of 1.04 individuals (of a total of 946 individuals) visit the new facility for maternal health care, which is less than the 2.39 individuals predicted by the measurement error model estimates; however, the difference is not statistically different from zero. A similar conclusion is reached for the CL model. For the second experiment, first note that for both the CL and ML models, the measurement error models predict that (i) a larger number of women visit the improved facilities pre-policy and (ii) the raw increase in visitors, pre- to post-policy, is larger. However, consistent with our hypothesis, the measurement error models predict a smaller percentage increase in the number of visitors due to the policy. For our preferred specification, the measurement error models predict a 54.6 percent increase in visitors to the improved facilities, while the models estimated using data measured without error predicts a 63.2 percent increase.

These results highlight a potential consequence of bias in preference parameter estimates due to measurement error. In our setting, we find that the measurement error model estimates would lead policy makers to overestimate the popularity of a new health facility and underestimate the popularity of improving existing facilities. This finding, that preference estimates which are biased toward a strong distaste for travel relative to preference for quality will lead policy makers to favor new facilities over improving existing ones, should be true generally, but only for new facilities that reduce travel costs for some women. The finding is important because policy-makers concerned with acquiring political capital already have an incentive to construct new buildings, which generally come at a high financial cost.

Table 6: Policy Experiments for Maternal Health Care Choices

	(1) CL - Measurement Error	(2) CL - Complete	(3) ML - Measurement Error	(4) ML - Complete
Experiment 1: New Facility				
Avg. patients visiting new fac.	6.25	5.17	2.39	1.04
	(2.60)	(2.42)	(1.47)	(1.08)
Experiment 2: Improved Facilities				
Avg. patients visiting pre-policy	20.49	13.33	11.79	3.66
Avg. patients visiting post-policy	40.56	31.79	18.23	5.98
% change	97.92	138.56	54.60	63.29
	(14.64)	(22.93)	(21.51)	(42.30)

*Notes: Standard errors are provided in parethesis. Table averages and standard errors are calculated from 500 simulation draws, which are described in section IV.e. Parameter estimates used for the CL simulations are taken from columns 1 and 3 of Table 4. Parameter estimates used for the ML simulations are taken from columns 2 and 4 of Table 4. Experiment 1 adds a new facility to every individual's alternative set. Experiment 2 adds electricity to the six facilities in Dakar that did not have it at the time of data collection.

V. Discussion

We estimate facility choice models for maternal health services for women living in urban Senegal. Compared to other research on health facility choice in developing countries, the research is unique in (i) our focus on women living in urban environments and (ii) our ability to match women to the health facility that they actually visit. We report two main findings from our preferred mixed logit model. First, we find that women dislike traveling long distances for medical care and that they prefer higher quality facilities. Among the many facility characteristics that women value, we consistently find strong preferences for facilities that are open seven days a week, have more doctors, offer a larger number of services, provide Information, Education, and Communication (IEC) materials, run community outreach programs, and have modern amenities, such as electricity, telephones, and private rooms. Second, we provide evidence that a particular type of measurement error that is common in the literature leads to biased preference estimates. In our setting, this measurement error leads to a significant overestimation of patient distaste for travel, relative to preferences for facility quality. Using a policy experiment that compares the effectiveness of a new health facility vs. improved existing facilities, we provide an important example of a consequence that can result from bias in preference parameter estimates.

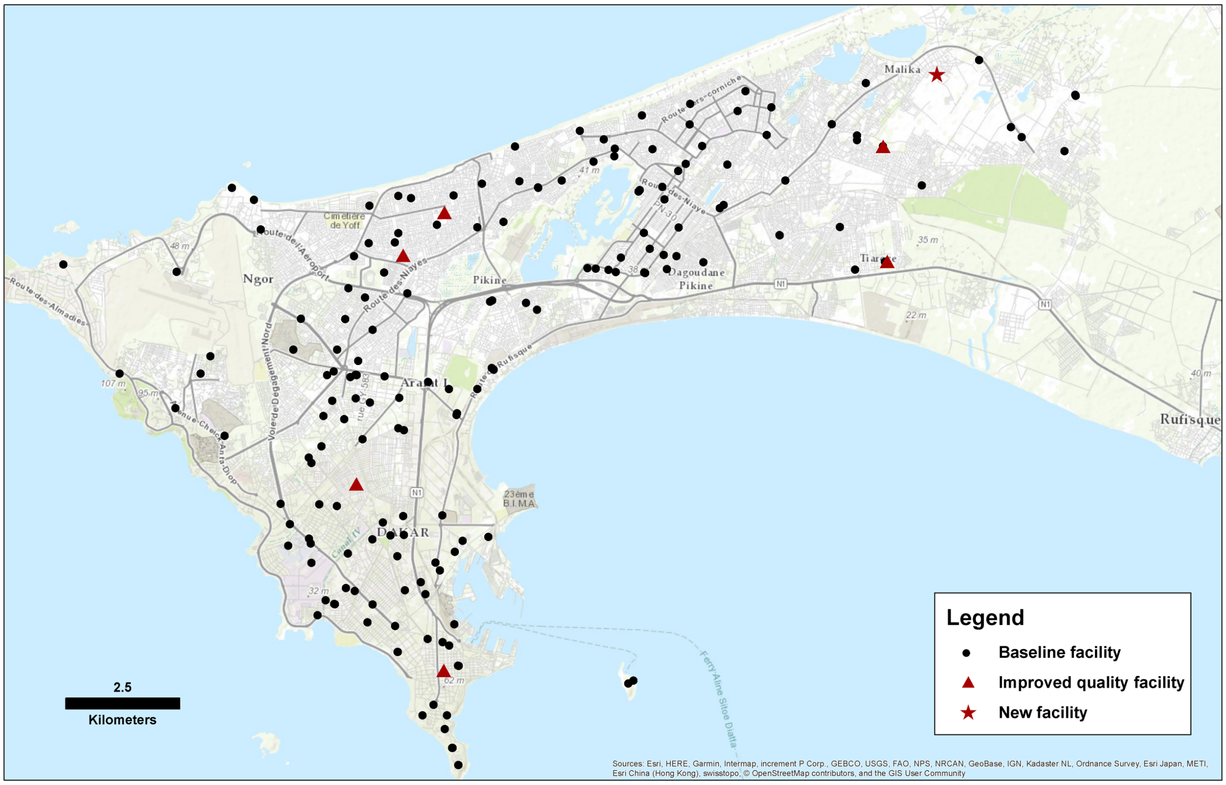
There are several limitations to our analysis. For example, while our results suggest how health facilities may be improved to attract more patients, we say nothing about the impact that these choices might have on services used or, more importantly, patient health, some of which is explored with these data in Cronin et al. (2018). Moreover, our model of demand abstracts from potential general equilibrium effects (i.e., facility characteristics are partially determined by market forces, such as consumer demand). It is also possible that unobserved quality characteristics, such as client-provider interaction details and prices for particular medical procedures, are correlated with observed characteristics. Both of these concerns could be mitigated with an experimental design that randomly altered the characteristics of some facilities, but not others. Finding willing (facility) participants for such an experiment is difficult, which likely explains why such experimental designs are rarely used in this literature.

This paper contributes to a large literature on facility choice in developing countries, most notably, by quantifying the bias in preference parameter estimates due to measurement error. The paper also contributes to a large literature on facility choice in *developed* countries, despite the fact that our population of study resides elsewhere. Compared to the developing country research referenced above, the developed country literature features quality metrics that are objective and well defined, such as facility-procedure specific mortality rates (Luft et al., 1990; Burns and Wholey, 1992; Hodgkin, 1996; Mukamel et al., 2004; Dranove and Sfekas, 2008), birth rates (Bundorf et al., 2009); remission rates (Varkevisser et al., 2012); and overall quality indexes (Santos et al., 2015). Moreover, much of the literature focuses not only on whether people respond to quality, but whether publicized report cards have an additional marginal impact on patient choice (Mukamel et al., 2004; Dranove and Sfekas, 2008; Bundorf et al., 2009; Werner et al., 2012). This literature finds, quite consistently, that patients respond to facility quality, with or without report cards (Kolstad and Chernew, 2009); however, in most instances studied, primary care physicians are likely to play a role in referring patients to facilities. Given the medical expertise and professional network of referring physicians, it is not terribly surprising that this research reveals a preference for quality, even in the absence of publicly available report cards.

While there are many economic and cultural differences between the choice environments studied in this paper and those studied in developed countries, this paper contributes to the larger facility choice literature in three important ways. First, given our focus on maternal health services, it is likely that the preferences revealed by our choice model reflect those of patients and not referring physicians. Second, because we measure preferences for facility characteristics that proxy for quality, rather than developing an index of quality, our findings shed light on which characteristics patients' value most for maternal health services and, therefore, should be useful in the future construction of quality indexes. Third, similar research in developed countries tends to extract choice information from administrative discharge data (e.g., Luft et al., 1990; Burns and Wholey, 1992; Hodgkin, 1996; Chernew et al., 1998; Mukamel et al., 2004; Dranove and Sfekas, 2008). An advantage of discharge data is that the issue of patient-facility mismatch is avoided; however, a disadvantage is that researchers only observe individuals who choose to visit a facility. Thus, the estimation sample is non-randomly selected and could produce biased parameter estimates if individuals not visiting a facility have preferences that differ from individuals visiting a facility. Our use of survey data, which contains information on women who choose not to visit a facility, enables us to control for this sample selection problem using a selection-on-observables strategy. Unfortunately, absent additional information on the composition of the population that chooses not to visit a facility, researchers that choose to use discharge data to estimate choice models cannot use this technique. That said, our results reveal minimal endogenous selection into the sample in our particular setting, providing some evidence that sample selection issues in similar settings are of minor concern.

Figures

Figure 1: Location of health facilities in the region of Dakar, Senegal



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Measurement Error in Discrete Health Facility Choice Models: an Example from Urban Senegal

Appendix

Christopher J. Cronin, David K. Guilkey, Ilene S. Speizer

A. Weighted vs. Unweighted Estimator

Wooldridge (2002) compares and contrasts the weighted and unweighted estimators. Under a set of regularity conditions, the unweighted estimator is consistent and asymptotically more efficient than the weighted estimator, if selection is *ignorable* conditional on control variables (i.e., $P(S_i = 3 | d_{ij}, X_{ij}) = P(S_i = 3 | X_{ij})$ where d_{ij} is an indicator variable that equals 1 if individual i selects facility j and 0 otherwise). Given our exclusion of individual-level controls, Z_i, from the facility choice model, we view this assumption to be too strong. Consistency of the weighted estimator requires that the same set of regularity conditions hold, but the ignorability assumption is weaker – selection must be *ignorable* conditional on control variables, X_{ij}, and additional observables, W_i $\left(\text{i.e., } P(S_i = 3 | d_{ij}, X_{ij}) = P(S_i = 3 | X_{ij}, W_i)\right)$. We define W_i using individual-level controls, Z_i, and interactions between individual and facility-specific controls.

The weighting strategy is intuitive. One way to describe the sample selection problem is that, without correction, our estimates will not capture the preferences of individuals not visiting a facility. By weighting choice probabilities by the inverse of the probability of inclusion, we give the choices/preferences of included individuals who look like (i.e., have similar observable characteristics as) excluded individuals greater weight in the estimation of the model's parameters. The estimated parameters then capture the preferences of the entire population, which is comprised of individuals both visiting and not visiting health facilities.

The existing developing country facility choice literature, which generally utilizes survey data featuring a subsample of people not visiting a facility, addresses sample selection using a different strategy. Researchers typically design choice models that (i) designate "no facility" as a choice alternative and (ii) allow individual-level characteristics (i.e., Z_i from our model) to have a separate impact on the indirect utility received from *every* choice alternative (Akin et al., 1986; Dor et al., 1987; Gertler et al., 1987; Mwabu et al., 1993; Akin et al., 1995; Bolduc et al., 1996; Mariko, 2003; Borah et al., 2006; Habtom and Ruys, 2007; Erlyana et al., 2011). This method controls for endogenous sample selection only if unobserved preferences for facilities, ϵ_{ij}, are independent across the sample conditional on the individual-level characteristics – a strong assumption. We prefer our weighting method to this alternative strategy for two reasons. First, the alternative strategy requires the estimation of $(J-1)*K$ additional parameters, where J is the number of alternatives and K is the number of individual-level controls. Thus, the method cannot be implemented with a large alternative set, nor can the method accommodate a large number of controls. Second, the alternative strategy does not allow the conditioning individual-level characteristics to include variables that are endogenous to selection. Both Wooldridge (2010, Ch. 19) and Moffitt et al. (1999) note that consistency of the weighted estimator does not require that W_i and ω_{ij} are uncorrelated. In other words, control variables that are endogenous to the facility choice model can be included in the selection equation to help satisfy the ignorability assumption. As such, we include such variables (e.g., pregnant, gave birth recently, number of children, fertility desires, etc.) in W_i. It is also the case that the asymptotic variance of the weighted estimator is decreasing in the number of control variables in the selection equation. For both of these reasons, Wooldridge (1999) recommends a "kitchen sink" approach, where the selection equation (Equation 3) is saturated with any controls thought potentially relevant to selection, along with interactions and polynomials of the control variables. We have taken this approach, which explains our large set of control variables in Table A1.

B. MLE Data Sampling Design

At baseline, in 2011, a multi-stage sampling design was used to select a representative sample of women ages 15-49 from six Urban sites in Senegal: Dakar, Guédiawaye, Pikine, Mbao, Mbour, and Kaolack. In the first stage, between 32 and 64 primary sampling units (PSUs) were selected based on the size of the urban site. PSUs were created based on the 2002 census sampling frame that was updated in

2009; details of the sampling frame can be found in the MLE baseline report (MLE and Initiative Sénégalaise de Santé Urbaine, ISSU, 2011). In the second stage, using a comprehensive listing of all households in a selected PSU, a random sample of 21 households were selected for the women's interview; men were also surveyed in half of the selected households. Household heads were asked to provide written consent for any eligible woman under age 18. The final response rate among women was 88.9%. In total, 9,614 women from 4,950 households were surveyed; this represents women from 263 primary sampling units across the six cities. In our analysis, 289 women were dropped due to missing individual-level information.

At baseline, data were collected from all public and private health facilities that offer maternal, newborn, child, and family planning services in each of the six cities. This included high capacity public hospitals as well as public and private health centers and dispensaries. Across the six cities, of a total of 269 health facilities on the master list, 231 were identified and survey data were collected from 205. Sixty-four facilities were not included due to reasons such as striking providers, being merged with another facility, not offering the relevant services, no longer in existence, and provider unavailable for interview. At each health facility, an audit was performed to obtain information on services offered, family planning methods available, and stockouts. Moreover, a provider interview was undertaken with up to four providers depending on the size of the facility. (For details, see the ISSU Final Report, 2012.)

C. Robustness – Alternative Set

In our main specification, facilities from the regions of Dakar (which contains the cities of Dakar, Guédiawaye, Pikine, and Mbao), Mbour, and Kaolack are included in every woman's alternative set, regardless of the region a woman resides in. This methodology assumes implicitly that women know of all facilities within the three regions and select a facility optimally based on the facility's characteristics and distance from their home. This assumption may be questionable, as Dakar is roughly 69 km from Mbour and 178 km from Kaolack, while Mbour is 109 km from Kaolack. If our assumption is incorrect, then parameters, particularly those on distance, will reflect some likelihood that women know about the facility, as well as their preference for travel. We test the validity of this assumption by estimating two additional mixed logit models. In the first, we leave the choice sets intact, but drop the 29 women that are observed to leave their home region for care. Shown in column 2 Table A3, this model reflects a slightly greater distaste for travel than the preferred model, which makes sense, given that long-distance travelers have been dropped; however, using a chi-squared test (i.e., Wald test statistic using 500 bootstrap draws as is described in Section IV.a of the manuscript) for a difference in the ratio of parameters in this model and our preferred model (i.e., parameters from Table 3, column 2), we are unable to reject the null hypothesis that the two sets of parameter estimates are the same. In a second specification, we again limit the sample to women staying within their own region, but also restrict each woman's alternative set to the facilities located in her home region. Results from this specification are presented in column 3 of Table A3. Again, using a chi-squared test, we fail to reject the null that these parameter estimates are different from those of our preferred specification. Given these results, our analyses include all women and allow choices from the full set of observable facilities.

D. Robustness - Prices

Historically, patients in urban Senegal have been charged a base user fee to see a healthcare provider, plus an additional fee-for-service performed. Yates (2009) suggests that user-fees were abolished in Senegal prior to 2009; however, Koster et al. (2016) clearly states that user-fees are the norm for prenatal services, with only 15% of the population having insurance coverage for these costs. Unfortunately, our data do not contain information on the price of delivery, prenatal, or postnatal care, which is likely an important determinant of the demand for care. Seeking to better understand the price environment, we spoke with researchers at Intrahealth International, a non-governmental organization based in Chapel Hill, NC, who have done extensive health-related work in Senegal. These discussions provided rough estimates of average user and delivery fees in our urban environment. According to Intrahealth International, user-fees average roughly 450 F CFA ($0.80 US) across provider types, while delivery fees vary significantly across provider types. For example, a normal delivery at a public hospital averages 7,500 F CFA; at a public health center or health post, 3,000 F CFA; at a private clinic, 300,000 F CFA for a normal delivery and 600,000 F CFA for a cesarean; at other private facilities, 30,000 F CFA. Average delivery prices at denominational and NGO clinics are less clear, but are under 15,000 F CFA.

In Section IV.c of the manuscript, we attempt to use this price information and the choices observed in our data to get a sense of the role prices play in patient demand for facilities. We begin by creating a price variable that equals the average delivery cost reported by Intrahealth International for each facility type. We then estimate a conditional logit model, including this price variable in place of facility type indicators (because there is no variation in price within a facility type, preferences for prices are not separately identified from preferences for facility types). Our findings, which are presented in column 1 of Table A5, clearly show a preference for lower prices.

To further explore the impact that missing prices have on our main findings, we also estimate a conditional logit model that includes as controls indicators for the full set of facility types observable in our data; public hospitals are excluded. These results are presented in column 2 of Table A5. All else equal, this specification reveals that women prefer low-price public health centers and health posts to moderately-priced public hospitals and moderately-priced public hospitals to high-priced private facilities, which is perfectly consistent with a preference for low prices. This specification also reveals very strong preferences for denominational and NGO clinics, which may be more expensive than public facilities, but are also likely to provide higher quality care. This specification provides three take-aways for our main specification. First, preferences for (i) the various types of public clinics, (ii) the various types of private clinics, and (iii) denominational and NGO clinics are similar. As such, it makes sense to define just four types of facilities – public hospitals, public clinics, private clinics, and denominational/NGO clinics. Second, estimated preferences for these various types of facilities are consistent with negative preferences for prices. Thus, the estimated facility type preference parameters should be interpreted as capturing a preference for prices, as well as preferences for unobserved facility type specific characteristics. Third, preferences for distance and the other facility quality measures are unaffected by the various strategies we have used to control for prices, providing some assurance that the omitted variable bias caused by missing prices is minimal.

E. Robustness - Preferred Model with Interactions

We expand our preferred mixed logit model to include interactions between facility and individual characteristics in order to determine whether estimated preference heterogeneity can be explained by observable characteristics. In column 1 of Table A6, we allow for preference heterogeneity by whether a woman resides in a household in the lower two income quintiles. In column 2, we allow for preference heterogeneity by whether the woman has received any formal education (40 percent have not). Understanding facility preferences for these two groups is particularly important for policy makers and public health officials, as low income and uneducated women are significantly less likely to visit a health facility for maternal care services.

Focusing first on preference heterogeneity by income, our results show that relative to middle/high income women, low income women have stronger preferences for a large number of offered services and nearby facilities, but weaker preferences for longer hours, social workers, community outreach, electricity, and private rooms. The distaste for travel among these women could reflect the financial cost associated with such travel, as well as a lack of transportation. Low education women also have stronger preferences for a large number of offered services, as well as telephones and private rooms, but weaker preferences for longer hours. Note that both disadvantaged groups have weaker preferences for facilities open all hours, which could reflect the fact that these women are less likely to work. Moreover, both low income and low education women have significantly weaker preference for private facilities, which likely reflects price sensitivity, as was discussed in the previous section.

Table A1: Multinomial Choice Models of Facility for Maternal Health Services

	(1) Unweighted, Cond. Logit		(2) Unweighted, Mixed Logit		(3) Weighted, Cond. Logit		(4) Weighted, Mixed Logit	
Covariates	Ratio	SE	Ratio	SE	Ratio	SE	Ratio	SE
Panel A: Mean Coefficients								
distance (km)	-1.000		-1.000		-1.000		-1.000	
public clinic	1.459	0.593	0.227	0.129	-0.245	1.383	0.863	1.353
private clinic	-4.648	1.532	-0.927	0.169	-5.727	2.990	-1.654	2.424
denominational/NGO clinic	3.631	1.100	0.550	0.174	5.759	2.219	0.830	0.546
age	0.056	0.013	0.010	0.001	0.091	0.034	0.015	0.004
open 7 days a week	2.251	0.752	0.442	0.108	4.364	1.799	0.967	0.263
hours a day	0.015	0.041	-0.001	0.006	-0.073	0.086	-0.012	0.014
# doctors	0.071	0.029	0.032	0.012	0.045	0.047	0.014	0.027
# nurses	-0.018	0.029	0.000	0.007	0.007	0.064	-0.006	0.016
# midwives	0.255	0.085	0.019	0.011	0.354	0.179	0.048	0.023
any health social worker	1.700	0.385	0.633	0.073	3.472	1.183	0.994	0.238
# services offered	0.416	0.130	0.073	0.018	0.618	0.308	0.107	0.037
any IEC materials	1.058	0.463	0.462	0.082	1.410	1.012	0.746	0.291
provides community outreach	2.230	0.768	0.254	0.076	0.890	1.147	0.134	0.176
has electricity	5.582	1.646	1.043	0.179	3.349	2.687	1.322	0.541
has telephone	3.211	0.727	0.629	0.085	3.460	1.527	0.828	0.260
has private rooms	5.099	1.318	0.988	0.164	2.242	2.429	1.087	0.624
participated in survey	-22.026	4.843	-4.454	0.452	-19.106	8.797	-2.413	1.848
Panel B: Std. Dev. of Coef.								
distance (km)			0.540	0.034			0.509	0.040
public clinic			0.138	0.293			2.916	2.243
private clinic			1.113	0.298			2.395	2.494
denominational/NGO clinic			0.274	0.175			0.037	0.714
age			0.002	0.001			0.005	0.009
open 7 days a week			0.006	0.084			0.033	0.352
hours a day			0.009	0.004			0.029	0.022
# doctors			0.005	0.015			0.045	0.029
# nurses			0.014	0.009			0.037	0.021
# midwives			0.009	0.004			0.016	0.010
any health social worker			0.083	0.065			0.190	0.246
# services offered			0.003	0.007			0.151	0.083
any IEC materials			0.001	0.092			0.419	0.622
provides community outreach			0.042	0.095			0.445	0.264
has electricity			0.038	0.122			1.069	0.574
has telephone			0.139	0.169			0.540	0.517
has private rooms			0.214	0.198			1.526	0.824
participated in survey			0.113	0.110			2.003	1.250
Number of Individuals	1,830		1,830		1,758		1,758	
Number of Obervations	422,730		422,730		406,098		406,098	
LLF	-6,921.388		-5,815.555		-29,296.947		-25,582.033	

*Notes: Conditional and mixed logit models are estimated using Stata packages *clogit* and *mixlogit*, respectively. In both models, the reference facility type is a public hospital. The mixed logit models are estimated via maximum simulated likelihood, using 50 Halton draws. Ratios of parameters, which are independent of scale and thus comparable across models, are reported. These ratios are formed by dividing the mean (and standard deviation) of preferences by the negative of the mean preference for distance. Ratios in panel A can be interpreted as the distance that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Ratio standard errors are calculated via bootstrap proceedure described in section IV.a.

Table A2: First Stage Selection Equation

Covariates	Params	SE
S_i = 3 (visit surveyed fac.)		
age	0.142	0.108
age squared	-0.002	0.001
SES quartile 2	-0.133	0.434
SES quartile 3	-0.138	0.435
SES quartile 4	-0.236	0.470
SES quartile 5 (highest)	-0.775	0.550
highest edu: primary school	-0.279	0.333
highest edu: middle school	-1.206	0.495
highest edu: high school	3.132	2.800
highest edu: college	4.311	2.976
Muslim	-0.810	0.693
# children at home	-0.025	0.138
currently pregnant	5.808	0.644
has given birth in last 2.5 years	3.402	0.370
have partner	1.671	1.258
partner has otherwives	0.277	0.412
is capable of getting pregnant	2.616	3.859
want more children	0.049	0.685
partner wants more children	-0.001	0.458
partner RARELY accompanies to HF	-0.770	0.497
partner SOMTIMES accompanies to HF	0.086	0.464
partner OFTEN accompanies to HF	-0.559	0.480
partner ALWAYS accompanies to HF	-0.301	0.891
partner age	-0.001	0.022
partner highest edu: none	0.164	0.393
partner highest edu: primary	0.259	0.546
partner highest edu: middle	0.640	0.621
partner highest edu: high	0.400	0.735
partner highest edu: college	2.764	0.785
partner works	0.514	0.644
currently working	-0.485	0.314
reads newspapers and/or magazines	0.671	0.423
listens to radio	-0.585	0.307
watches television	-0.760	0.624
has own personal cell phone	0.598	0.311
has internet access	-0.989	0.574
owns a car	0.400	0.466
owns a scooter	0.121	0.458
owns a bicycle	0.299	0.637
home city: Guediawaye	-0.664	0.515

home city: Pikine	-0.672	0.565
home city: Mbao	-0.310	0.581
home city: Mbour	-0.944	0.519
home city: Kaolack	-0.891	0.482
# public hospitals	-0.085	0.189
# public clinics	0.089	0.052
# private clinics	-0.056	0.065
# denominational/NGO clinics	0.293	0.087
# pharmacies	-0.013	0.012
all facilities not participating	0.111	0.299
HF: average distance	0.008	0.007
HF: average age	0.003	0.005
HF: # open every day	0.057	0.061
HF: average hours open per day	-0.024	0.012
HF: average # doctors	-0.311	0.086
HF: average # nurses	-0.012	0.030
HF: average # midwives	0.274	0.060
HF: average # staff	-0.065	0.027
HF: # health social workers	-0.122	0.086
HF: average # services offered	0.034	0.028
HF: average # FP methods available	-0.073	0.046
HF: % with stockout in prior 30 days	-0.044	0.206
HF: average # IEC tools per facility	-0.182	0.062
HF: # that have ever given FP talk	-0.184	0.068
HF: proportion with FP protocol	-0.249	0.174
HF: proportion with electricity	-0.436	0.544
HF: proportion with piped water	0.486	0.650
HF: proportion with telephone	0.070	0.194
HF: proportion with private rooms	0.893	0.343
age * SES quartile 2	0.004	0.014
age * SES quartile 3	0.004	0.014
age * SES quartile 4	0.009	0.015
age * SES quartile 5 (highest)	0.025	0.018
age * highest edu: primary school	0.013	0.011
age * highest edu: middle school	0.043	0.016
age * highest edu: high school	-0.268	0.150
age * highest edu: college	-0.315	0.156
age * Muslim	0.016	0.022
age * # children at home	0.002	0.004
age * currently pregnant	-0.083	0.021
age * has given birth in last 2.5 years	-0.051	0.012
age * have partner	-0.029	0.041
age * partner has otherwives	-0.010	0.012
age * is capable of getting pregnant	-0.036	0.085
age * want more children	-0.003	0.019

age * partner wants more children	0.002	0.014
age * partner RARELY accompanies to HF	0.018	0.016
age * partner SOMTIMES accompanies to HF	0.000	0.015
age * partner OFTEN accompanies to HF	0.015	0.015
age * partner ALWAYS accompanies to HF	0.015	0.027
age * partner age	0.000	0.001
age * partner highest edu: none	-0.010	0.013
age * partner highest edu: primary	-0.011	0.018
age * partner highest edu: middle	-0.012	0.019
age * partner highest edu: high	-0.013	0.023
age * partner highest edu: college	-0.087	0.025
age * partner works	-0.004	0.019
age * currently working	0.011	0.010
age * reads newspapers and/or magazines	-0.017	0.014
age * listens to radio	0.022	0.010
age * watches television	0.024	0.020
age * has own personal cell phone	-0.020	0.010
age * has internet access	0.034	0.019
age * owns a car	-0.015	0.015
age * owns a scooter	-0.007	0.015
age * owns a bicycle	-0.013	0.020
age * home city: Guediawaye	0.027	0.016
age * home city: Pikine	-0.006	0.018
age * home city: Mbao	-0.016	0.018
age * home city: Mbour	0.000	0.015
age * home city: Kaolack	0.012	0.014
age * average HF distance	0.000	0.000
edu * age squared	0.005	0.002
edu * SES quartile 2	-0.114	0.664
edu * SES quartile 3	0.293	0.633
edu * SES quartile 4	0.577	0.602
edu * SES quartile 5 (highest)	-0.225	0.630
edu * Muslim	0.143	0.419
edu * # children at home	-0.308	0.150
edu * currently pregnant	15.681	690.161
edu * has given birth in last 2.5 years	0.486	0.354
edu * have partner	3.010	1.519
edu * partner has otherwives	0.067	0.417
edu * is capable of getting pregnant	-2.137	1.366
edu * want more children	0.834	0.568
edu * partner wants more children	-1.884	0.538
edu * partner RARELY accompanies to HF	0.292	0.484
edu * partner SOMTIMES accompanies to HF	0.584	0.483
edu * partner OFTEN accompanies to HF	-0.109	0.440
edu * partner ALWAYS accompanies to HF	0.749	0.625

edu * partner age	-0.036	0.027
edu * partner highest edu: none	0.286	0.692
edu * partner highest edu: primary	-0.124	0.720
edu * partner highest edu: middle	-0.705	0.660
edu * partner highest edu: high	0.036	0.617
edu * partner highest edu: college	-0.290	0.590
edu * partner works	0.379	0.705
edu * currently working	-0.047	0.300
edu * reads newspapers and/or magazines	-0.073	0.376
edu * listens to radio	0.334	0.322
edu * watches television	-0.502	1.060
edu * has own personal cell phone	1.460	0.975
edu * has internet access	0.183	0.330
edu * owns a car	-0.151	0.357
edu * owns a scooter	0.335	0.423
edu * owns a bicycle	0.064	0.491
edu * home city: Guediawaye	0.226	0.391
edu * home city: Pikine	-0.763	0.573
edu * home city: Mbao	0.503	0.517
edu * home city: Mbour	0.088	0.393
edu * home city: Kaolack	-0.734	0.388
edu * average HF distance	-0.016	0.012
constant	-6.184	4.098
S_i = 2 (visit non-surveyed fac.)		
age	0.637	0.973
age squared	-0.001	0.002
SES quartile 2	0.555	0.787
SES quartile 3	0.318	0.775
SES quartile 4	0.114	0.824
SES quartile 5 (highest)	0.625	0.914
highest edu: primary school	0.120	0.560
highest edu: middle school	0.189	0.790
highest edu: high school	-21.562	1602.851
highest edu: college	-21.093	1602.852
Muslim	-0.924	1.115
# children at home	-0.187	0.229
currently pregnant	4.980	0.826
has given birth in last 2.5 years	4.103	0.620
have partner	1.546	2.100
partner has otherwives	0.240	0.652
is capable of getting pregnant	33.187	46.096
want more children	-1.381	1.094
partner wants more children	-0.441	0.723
partner RARELY accompanies to HF	-2.012	0.798
partner SOMTIMES accompanies to HF	-0.136	0.699

partner OFTEN accompanies to HF	0.152	0.807
partner ALWAYS accompanies to HF	-1.662	1.488
partner age	0.018	0.035
partner highest edu: none	0.041	0.627
partner highest edu: primary	-0.868	0.886
partner highest edu: middle	0.362	1.045
partner highest edu: high	-1.013	1.174
partner highest edu: college	1.314	1.200
partner works	1.809	1.119
currently working	-0.476	0.534
reads newspapers and/or magazines	-0.842	0.689
listens to radio	-0.650	0.514
watches television	-2.051	1.288
has own personal cell phone	-0.278	0.540
has internet access	0.152	0.946
owns a car	0.598	0.732
owns a scooter	0.745	0.803
owns a bicycle	0.594	0.913
home city: Guediawaye	0.044	0.996
home city: Pikine	0.420	0.927
home city: Mbao	0.260	0.898
home city: Mbour	-0.735	0.900
home city: Kaolack	-0.138	0.926
# public hospitals	-0.028	0.345
# public clinics	-0.012	0.085
# private clinics	0.216	0.111
# denominational/NGO clinics	0.009	0.154
# pharmacies	0.006	0.021
all facilities not participating	-0.773	0.403
HF: average distance	0.007	0.011
HF: average age	-0.004	0.008
HF: # open every day	-0.122	0.110
HF: average hours open per day	-0.074	0.020
HF: average # doctors	-0.260	0.149
HF: average # nurses	-0.074	0.051
HF: average # midwives	0.421	0.102
HF: average # staff	-0.068	0.050
HF: # health social workers	0.000	0.149
HF: average # services offered	0.010	0.047
HF: average # FP methods available	0.055	0.080
HF: % with stockout in prior 30 days	0.436	0.329
HF: average # IEC tools per facility	-0.007	0.101
HF: # that have ever given FP talk	-0.178	0.111
HF: proportion with FP protocol	-1.500	0.283
HF: proportion with electricity	-0.679	1.013

HF: proportion with piped water	2.280	1.156
HF: proportion with telephone	-1.313	0.308
HF: proportion with private rooms	0.529	0.570
age * SES quartile 2	-0.009	0.027
age * SES quartile 3	-0.001	0.027
age * SES quartile 4	0.011	0.028
age * SES quartile 5 (highest)	-0.004	0.031
age * highest edu: primary school	0.001	0.019
age * highest edu: middle school	0.000	0.027
age * highest edu: high school	-0.128	0.236
age * highest edu: college	-0.118	0.249
age * Muslim	0.008	0.035
age * # children at home	0.004	0.007
age * currently pregnant	-0.051	0.028
age * has given birth in last 2.5 years	-0.074	0.020
age * have partner	-0.035	0.070
age * partner has otherwives	-0.002	0.020
age * is capable of getting pregnant	-0.677	0.961
age * want more children	0.035	0.031
age * partner wants more children	0.021	0.023
age * partner RARELY accompanies to HF	0.060	0.026
age * partner SOMTIMES accompanies to HF	0.010	0.023
age * partner OFTEN accompanies to HF	-0.012	0.027
age * partner ALWAYS accompanies to HF	0.052	0.047
age * partner age	0.000	0.001
age * partner highest edu: none	-0.006	0.021
age * partner highest edu: primary	0.025	0.029
age * partner highest edu: middle	-0.009	0.033
age * partner highest edu: high	0.032	0.036
age * partner highest edu: college	-0.036	0.039
age * partner works	-0.047	0.032
age * currently working	0.006	0.017
age * reads newspapers and/or magazines	0.037	0.022
age * listens to radio	0.029	0.018
age * watches television	0.085	0.047
age * has own personal cell phone	0.014	0.019
age * has internet access	0.000	0.034
age * owns a car	-0.023	0.024
age * owns a scooter	-0.034	0.028
age * owns a bicycle	0.005	0.030
age * home city: Guediawaye	0.021	0.032
age * home city: Pikine	0.005	0.030
age * home city: Mbao	0.011	0.027
age * home city: Mbour	0.016	0.026
age * home city: Kaolack	-0.016	0.029

age * average HF distance	0.000	0.000
edu * age squared	0.001	0.004
edu * SES quartile 2	-1.285	0.884
edu * SES quartile 3	-1.418	0.857
edu * SES quartile 4	-1.015	0.768
edu * SES quartile 5 (highest)	-1.214	0.792
edu * Muslim	1.164	0.645
edu * # children at home	0.370	0.250
edu * currently pregnant	16.315	690.161
edu * has given birth in last 2.5 years	0.750	0.538
edu * have partner	5.586	2.253
edu * partner has otherwives	0.590	0.655
edu * is capable of getting pregnant	9.920	1508.675
edu * want more children	0.093	0.820
edu * partner wants more children	-2.132	0.725
edu * partner RARELY accompanies to HF	-0.287	0.800
edu * partner SOMTIMES accompanies to HF	0.364	0.688
edu * partner OFTEN accompanies to HF	-1.376	0.785
edu * partner ALWAYS accompanies to HF	1.610	0.840
edu * partner age	-0.105	0.044
edu * partner highest edu: none	0.730	1.163
edu * partner highest edu: primary	0.077	1.126
edu * partner highest edu: middle	-0.929	1.255
edu * partner highest edu: high	0.051	1.105
edu * partner highest edu: college	0.385	1.012
edu * partner works	-0.948	0.949
edu * currently working	0.206	0.442
edu * reads newspapers and/or magazines	-0.683	0.541
edu * listens to radio	0.403	0.487
edu * watches television	-0.097	1.537
edu * has own personal cell phone	15.388	541.316
edu * has internet access	0.534	0.518
edu * owns a car	-0.094	0.505
edu * owns a scooter	-0.726	0.856
edu * owns a bicycle	-0.753	0.720
edu * home city: Guediawaye	-1.050	0.719
edu * home city: Pikine	-1.483	0.763
edu * home city: Mbao	0.243	0.591
edu * home city: Mbour	-2.245	0.741
edu * home city: Kaolack	-2.152	0.755
edu * average HF distance	-0.027	0.023
constant	-35.016	46.222
Overall chi-squared test statistic	3,981.290	0.000
Pseudo R-squared	0.324	
LLF	-4,146.125	

Number of Individuals	9,325

*Notes: This multinomial logit model is estimated with three alternatives: (S=1) individual visits no facility (baseline), (S=2) individual visits non-surveyed facility, (S=3) individual visits surveyed facility. The education interaction variable is an indicator for having obtained a highschool or college degree. The excluded category for partner's education is "don't know." The excluded city is Dakar.

Table A3: Mixed Logit Model - Robustness

	(1)		(2)		(3)	
Covariates	Ratio	SE	Ratio	SE	Ratio	SE
Panel A: Mean Coefficients						
distance (km)	-1.000		-1.000		-1.000	
public clinic	0.292	0.132	0.283	0.145	-0.033	0.369
private clinic	-0.520	0.225	-0.796	0.216	-0.879	1.052
denominational/NGO clinic	0.584	0.183	0.576	0.167	0.273	0.448
age	0.010	0.001	0.010	0.001	0.009	0.003
open 7 days a week	0.416	0.108	0.425	0.106	0.251	0.183
hours a day	0.003	0.006	-0.002	0.006	-0.001	0.010
# doctors	0.035	0.010	0.032	0.012	0.020	0.015
# nurses	-0.011	0.008	0.003	0.007	-0.006	0.012
# midwives	0.019	0.012	0.014	0.012	0.028	0.016
any health social worker	0.666	0.075	0.610	0.072	0.383	0.164
# services offered	0.090	0.021	0.072	0.017	0.054	0.024
any IEC materials	0.467	0.086	0.451	0.081	0.358	0.213
provides community outreach	0.302	0.076	0.230	0.074	0.254	0.132
has electricity	2.500	0.120	0.992	0.173	0.603	0.407
has telephone	0.843	0.082	0.602	0.081	0.441	0.167
has private rooms	1.442	0.146	0.956	0.165	0.700	0.551
participated in survey			-4.339	0.457	-3.095	1.138
Panel B: Std. Dev. of Coef.						
distance (km)	0.531	0.040	0.556	0.229	0.866	0.663
public clinic	0.497	0.302	0.425	0.364	0.075	0.905
private clinic	0.289	0.376	0.993	0.335	0.982	1.160
denominational/NGO clinic	0.297	0.223	0.011	0.165	0.159	0.626
age	0.003	0.001	0.001	0.001	0.001	0.005
open 7 days a week	0.211	0.127	0.201	0.075	0.127	0.356
hours a day	0.004	0.015	0.001	0.004	0.011	0.018
# doctors	0.003	0.014	0.001	0.016	0.001	0.019
# nurses	0.033	0.011	0.011	0.010	0.015	0.013
# midwives	0.007	0.005	0.001	0.004	0.002	0.012
any health social worker	0.119	0.074	0.148	0.055	0.123	0.175
# services offered	0.066	0.021	0.003	0.008	0.014	0.050
any IEC materials	0.002	0.112	0.132	0.094	0.025	0.434
provides community outreach	0.236	0.091	0.021	0.108	0.055	0.231
has electricity	1.946	0.108	0.036	0.124	0.051	0.406
has telephone	0.885	0.081	0.106	0.188	0.103	0.407
has private rooms	1.164	0.115	0.182	0.192	0.036	0.709
participated in survey			0.039	0.091	0.185	0.672
Number of Individuals	1,770		1,801		1,801	
Number of Obervations	362,850		416,031		194,357	
LLF	-5,522.44		-5,550.46		-5,224.64	

*Notes: All models are estimated using the *mixlogit* package in Stata, which uses maximum simulated likelihood, with 50 Halton draws. The reference facility type is a public hospital. Ratios of preference parameters, which are independent of scale, are reported. Ratios are formed by dividing the mean (and standard deviation) of the preference parameters by the negative of the mean preference for distance. Ratios in panel A (column 2) can be interpreted as the distance that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Ratio standard errors are calculated via bootstrap proceedure described in section IV.a. The reference facility type is a public hospital. These results should be compared to the baseline unweighted mixed logit model presented in column 2 of Table 3. Column 1 treats all non-participating facilities as non-identified and drops the 60 individuals selecting these facilities. Column 2 drops the 29 women who leave their home region to seek care. Column 3 also drops these 29 women, as well as constraining every woman's alternative set to the facilities located in her home region.

Table A4: Mixed Logit Model, 400 Halton draws

Covariates	Params	SE
Panel A: Mean Coefficients		
distance (km)	-1.094	0.058
public clinic	0.217	0.162
private clinic	-0.747	0.359
denominational/NGO clinic	0.451	0.176
age	0.011	0.001
open 7 days a week	0.456	0.107
hours a day	0.000	0.006
# doctors	-0.002	0.012
# nurses	-0.005	0.008
# midwives	0.032	0.013
any health social worker	0.704	0.075
# services offered	0.079	0.017
any IEC materials	0.525	0.083
provides community outreach	0.246	0.074
has electricity	1.141	0.185
has telephone	0.686	0.076
has private rooms	1.028	0.159
participated in survey	-4.837	0.414
Panel B: Std. Dev. of Coef.		
distance (km)	0.654	0.037
public clinic	0.801	0.404
private clinic	0.633	0.694
denominational/NGO clinic	0.085	0.097
age	0.000	0.001
open 7 days a week	0.010	0.090
hours a day	0.002	0.005
# doctors	0.047	0.010
# nurses	0.027	0.009
# midwives	0.001	0.004
any health social worker	0.021	0.061
# services offered	0.000	0.007
any IEC materials	0.080	0.127
provides community outreach	0.092	0.116
has electricity	0.010	0.087
has telephone	0.267	0.327
has private rooms	0.024	0.199
participated in survey	0.006	0.044
Number of Individuals	1,830	
Number of Obervations	422,730	
LLF	-5,795.62	

*Notes: All models are estimated using the *mixlogit* package in Stata with 400 Halton draws. The reference facility type is a public hospital. These results should be compared to the baseline unweighted, unscaled mixed logit model presented in column 1 of Table 3, which uses 50 Halton draws in estimation.

Table A5: Conditional Logit Model - Price Effects

	(1)		(2)	
Covariates	Ratio	SE	Ratio	SE
Panel A: Mean Coefficients				
distance (km)	-1.000		-1.000	
price (1,000 F CFA)	-0.020	0.005		
Facility Type				
public health center			1.725	0.629
public health post			1.031	0.737
other public			0.843	1.276
private clinic			-5.233	1.591
other private			-4.986	1.296
denominational clinic			1.821	2.140
NGO Clinic			4.389	1.655
age	0.054	0.013	0.055	0.014
open 7 days a week	2.040	0.735	2.277	0.755
hours a day	0.007	0.041	0.010	0.041
# doctors	0.044	0.024	0.077	0.030
# nurses	-0.025	0.029	-0.010	0.029
# midwives	0.291	0.090	0.223	0.089
any health social worker	1.716	0.388	1.352	0.449
# services offered	0.355	0.125	0.427	0.144
any IEC materials	1.114	0.443	0.854	0.459
provides community outreach	2.366	0.749	2.195	0.769
has electricity	5.544	1.621	5.478	1.632
has telephone	3.249	0.705	3.159	0.710
has private rooms	5.150	1.313	5.025	1.257
participated in survey	-20.636	4.621	-21.649	5.022
Number of Individuals	1,830		1,830	
Number of Obervations	422,730		422,730	
LLF	-6,936.90		-6,919.17	

*Notes: These models are estimated using the package *clogit* in Stata. Column 1 excludes all facility type indicators and includes a price variable; the construction of which is discussed in Appendix section IV of the manuscript. Column 2 contains the original facility type indicators. In column 2, he reference facility type is a public hospital. All results are presented as ratios of preference parameters (facility characteristics-to-distance), which are independent of scale. Ratio standard errors are calculated via bootstrap proceedure described in section IV.a.

Table A6: Mixed Logit Model - Preference Heterogeneity

	(1) Income Heterogeneity		(2) Education Heterogeneity	
Covariates	Ratio	SE	Ratio	SE
Panel A: Mean Coefficient				
distance (km) * low inc/edu	-0.251	0.071	-0.007	0.067
public clinic * low inc/edu	0.329	0.282	0.583	0.212
private clinic * low inc/edu	-1.244	0.407	-0.718	0.314
denominational/NGO clinic * low inc/edu	0.079	0.395	0.204	0.326
age * low inc/edu	0.002	0.003	-0.002	0.003
open 7 days a week * low inc/edu	-0.148	0.218	0.338	0.195
hours a day * low inc/edu	-0.032	0.013	-0.029	0.012
# doctors * low inc/edu	-0.016	0.013	-0.008	0.012
# nurses * low inc/edu	-0.004	0.014	-0.010	0.011
# midwives * low inc/edu	0.027	0.025	0.016	0.022
any health social worker * low inc/edu	-0.290	0.150	0.091	0.139
# services offered * low inc/edu	0.096	0.037	0.054	0.032
any IEC materials * low inc/edu	0.119	0.169	0.086	0.161
provides community outreach * low inc/edu	-0.301	0.157	-0.087	0.136
has electricity * low inc/edu	-0.764	0.418	0.107	0.318
has telephone * low inc/edu	-0.161	0.161	0.261	0.134
has private rooms * low inc/edu	-0.947	0.347	0.628	0.315
participated in survey * low inc/edu	0.209	0.885	-1.593	0.758
distance (km)	-1.000		-1.000	
public clinic	0.113	0.192	-0.004	0.155
private clinic	-0.427	0.233	-0.804	0.207
denominational/NGO clinic	0.510	0.236	0.452	0.210
age	0.010	0.002	0.010	0.002
open 7 days a week	0.506	0.167	0.281	0.139
hours a day	0.015	0.010	0.013	0.009
# doctors	0.038	0.011	0.034	0.010
# nurses	-0.001	0.009	0.003	0.008
# midwives	0.010	0.014	0.015	0.014
any health social worker	0.797	0.104	0.607	0.098
# services offered	0.040	0.023	0.050	0.021
any IEC materials	0.456	0.100	0.433	0.101
provides community outreach	0.416	0.111	0.280	0.087
has electricity	1.533	0.323	1.007	0.221
has telephone	0.753	0.123	0.541	0.111
has private rooms	1.512	0.282	0.770	0.184
participated in survey	-5.078	0.675	-3.870	0.496
Panel B: Std. Dev. of Coef.				
distance (km)	0.680	0.032	0.542	0.035
public clinic	0.483	0.404	0.048	0.331
private clinic	0.747	0.392	1.209	0.327

denominational/NGO clinic	0.285	0.161	0.266	0.170
age	0.002	0.001	0.002	0.001
open 7 days a week	0.147	0.091	0.002	0.092
hours a day	0.008	0.005	0.010	0.005
# doctors	0.002	0.016	0.005	0.013
# nurses	0.019	0.010	0.014	0.010
# midwives	0.014	0.005	0.008	0.004
any health social worker	0.056	0.085	0.077	0.067
# services offered	0.004	0.007	0.003	0.006
any IEC materials	0.287	0.097	0.003	0.097
provides community outreach	0.109	0.102	0.040	0.108
has electricity	0.100	0.133	0.043	0.117
has telephone	0.267	0.268	0.168	0.237
has private rooms	0.180	0.232	0.218	0.195
participated in survey	0.079	0.154	0.113	0.136
Number of Individuals	1,830		1,830	
Number of Obervations	422,730		422,730	
LLF	-5,749.39		-5,785.46	

*Notes: These models are estimated using the *mixlogit* package in Stata. In both models, the reference facility type is public hospital. Ratios of preference parameters, which are independent of scale, are reported. Ratios are formed by dividing the mean (and standard deviation) of the preference parameters by the negative of the mean preference for distance. Ratios in panel A (column 2) can be interpreted as the distance that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Ratio standard errors are calculated via bootstrap proceedure described in section IV.a. Column 1 allows mean preference parameters to vary by whether or not a woman's household is low income, which is defined as the lower two quintiles of the household income distribution. Column 2 allows mean preference paramete to vary by whether or not the woman has completed *any* education - 40 percent of adult women in our sample have

Table A7: Mixed Logit Model - Measurement Error vs. Complete Data, Alternative Specification

	(1) Mixed Logit, Meas. Error Data		(2) Mixed Logit, Complete Data	
Covariates	Ratio	SE	Ratio	SE
Panel A: Mean Coefficients				
distance (km)	-1.000		-1.000	
price	-0.217	0.079	-0.002	0.002
age	0.006	0.006	0.009	0.002
open 7 days a week	-0.252	0.450	0.409	0.107
hours a day	-0.009	0.023	-0.001	0.007
# doctors	0.006	0.036	0.004	0.013
# nurses	0.016	0.021	-0.007	0.007
# midwives	-0.029	0.032	0.032	0.014
any health social worker	0.279	0.329	0.661	0.075
# services offered	-0.001	0.045	0.067	0.018
any IEC materials	0.343	0.348	0.504	0.084
provides community outreach	0.646	0.243	0.291	0.085
has electricity	0.447	0.387	1.065	0.201
has telephone	0.077	0.276	0.655	0.090
has private rooms	-0.294	0.346	0.978	0.198
participated in survey	-0.415	1.150	-4.247	0.513
Panel B: Std. Dev. of Coef.				
distance (km)	0.506	0.075	0.601	0.035
price	0.691	0.056	0.000	0.002
age	4.081	0.013	0.002	0.002
open 7 days a week	3.756	0.494	0.180	0.086
hours a day	6.791	0.037	0.011	0.011
# doctors	6.615	0.039	0.036	0.016
# nurses	0.219	0.016	0.026	0.009
# midwives	0.649	0.025	0.013	0.006
any health social worker	2.828	0.489	0.044	0.082
# services offered	16.974	0.029	0.021	0.008
any IEC materials	0.434	0.180	0.120	0.104
provides community outreach	0.035	0.178	0.308	0.086
has electricity	0.242	1.280	0.047	0.100
has telephone	4.637	0.273	0.319	0.197
has private rooms	0.757	0.373	0.212	0.235
participated in survey	0.678	1.969	0.112	0.105
Number of Individuals	1,830		1,830	
Number of Obervations	7,320		422,730	
LLF	-1,332.37		-5,813.02	

*Notes: These models are estimated using the *mixlogit* package in Stata. Ratios of preference parameters, which are independent of scale, are reported. Ratios are formed by dividing the mean (and standard deviation) of the preference parameters by the negative of the mean preference for distance. Ratios in panel A (column 2) can be interpreted as the distance that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Ratios in panel B measure the standard deviation of this willingness to travel, for an individual having mean travel preferences. Ratio standard errors are calculated via bootstrap proceedure described in section IV.a. Column 1 does not include any facility type indicators, but does include the price variable described in section IV.c. Column 1 uses mismeasured data described in section IV.d, while column 2 uses the complete dataset described in Section III.

Table A8: Mixed Logit Model Estimates - Measurement Error Experiments

	(1)	(2)	(3)	(4)	(5)	(6)
Preferences						
distance	-1.038	-0.014	-0.282	-5.708	-2.802	-2.567
	(0.055)	(0.003)	(0.105)	(0.249)	(0.087)	(0.178)
any health social worker	1.225	0.446	1.043	0.793	0.485	0.638
	(0.052)	(0.052)	(0.066)	(0.114)	(0.134)	(0.129)
ratio	1.180	32.076	3.694	0.139	0.173	0.249
Number of Individuals	1,830	1,830	1,830	1,830	1,830	1,830
Number of Obervations	422,730	8,441	37,199	422,730	422,730	7,320
LLF	-6,494.23	-2775.4035	-5043.2876	-2,951.04	-4,191.85	-1,671.49

*Notes: All models are estimated using the *mixlogit* package in Stata. The estimated mean of the parameter distribution is reported in the first two rows. Ratios are formd by dividing the mean preference estimate for any health social worker by the negative of the mean distance preference estiamted. The ratio is interpreted as the distance that an individual is willing to travel to acquire one more unit of the given facility attribute, for an individual having mean preferences for both distance and the attribute. Thus, a small ratio reflects a strong distaste for travel. Column 1 allows choice from the full alternate set and matches individuals to their reported facility. Column 2 allows choice from an alternative set defined by the nearest facility of each type, plus the repored facility, and matches individuals to their reported facility. Column 3 allows choice from an alternative set defined by the nearest five facilities of each type, plus the repored facility, and matches individuals to their reported facility. Column 4 allows choice from the full alternate set and matches individuals to the nearest reported facility. Column 5 allows choice from the full alternate set and matches individuals randomly to one of the three nearest facilities of the reported type. Column 6 allows choice from an alternative set defined by the nearest facility of each type and matches individuals to the nearest reported facility.

Table A9: Conditional Logit Model with Individual Controls, Mismeasured Data

	(1) Unweighted, Conditional Logit		(2) Unweighted, Conditional Logit	
Covariates	Params	SE	Ratio	SE
Facility Attributes				
distance (km)	-0.468	0.070	-1.000	
age	0.002	0.004	0.004	0.008
open 7 days a week	-0.316	0.206	-0.676	0.514
hours a day	-0.009	0.012	-0.019	0.031
# doctors	-0.002	0.009	-0.004	0.024
# nurses	0.001	0.014	0.002	0.032
# midwives	0.017	0.021	0.036	0.055
any health social worker	0.076	0.188	0.162	0.470
# services offered	0.045	0.022	0.097	0.060
any IEC materials	0.012	0.209	0.025	0.435
provides community outreach	0.146	0.164	0.311	0.362
has electricity	0.203	0.231	0.433	0.589
has telephone	0.157	0.155	0.336	0.369
has private rooms	-0.235	0.236	-0.502	0.576
participated in survey	-0.439	0.460	-0.938	1.141
Facility Type				
Public Clinic	2.594	0.683	5.547	2.179
* (woman's) age	-0.031	0.011	-0.066	0.027
* primary education	-0.129	0.188	-0.277	0.412
* middle school education or more	-0.697	0.219	-1.491	0.507
* muslim	-0.220	0.428	-0.470	1.031
* employed	0.198	0.177	0.424	0.390
* owns car, scooter, or bicycle	-0.040	0.216	-0.085	0.519
* Guediawaye	0.345	0.507	0.738	1.257
* Pikine	1.292	0.547	2.762	1.547
* Mbao	1.116	0.560	2.387	1.555
* Mbour	0.207	0.338	0.443	0.867
* Kaolack	0.743	0.459	1.589	1.153
* second SES quintile	-0.301	0.265	-0.643	0.621
* third SES quintile	-0.606	0.252	-1.295	0.678
* fourth SES quintile	-0.295	0.283	-0.631	0.667
* fifth SES quintile	-0.943	0.305	-2.016	0.829
Private Clinic	-1.670	0.884	-3.571	2.296
* (woman's) age	0.014	0.016	0.029	0.038
* primary education	0.456	0.307	0.975	0.744
* middle school education or more	0.666	0.327	1.424	0.898
* muslim	-0.977	0.543	-2.088	1.223
* employed	-0.170	0.278	-0.363	0.704
* owns car, scooter, or bicycle	0.074	0.296	0.159	0.656

* Guediawaye	0.355	0.587	0.760	1.450
* Pikine	0.833	0.646	1.781	1.664
* Mbao	0.817	0.694	1.747	1.744
* Mbour	-0.379	0.447	-0.811	1.080
* Kaolack	1.435	0.508	3.069	1.208
* second SES quintile	-0.022	0.560	-0.048	1.301
* third SES quintile	0.546	0.499	1.167	1.282
* fourth SES quintile	1.085	0.510	2.320	1.306
* fifth SES quintile	1.107	0.524	2.368	1.322
Denomnational/NGO Clinic	-0.521	0.843	-1.115	2.169
* (woman's) age	0.023	0.018	0.049	0.045
* primary education	0.269	0.303	0.576	0.664
* middle school education or more	-0.043	0.355	-0.092	0.758
* muslim	-1.269	0.553	-2.713	1.453
* employed	0.156	0.279	0.334	0.672
* owns car, scooter, or bicycle	-0.055	0.340	-0.117	0.714
* Guediawaye	-1.018	0.643	-2.176	1.579
* Pikine	-1.516	1.132	-3.241	13.378
* Mbao	0.339	0.603	0.725	1.483
* Mbour	21.585	3.808	46.151	32.213
* Kaolack	0.763	0.504	1.630	1.200
* second SES quintile	0.351	0.442	0.751	1.007
* third SES quintile	0.188	0.432	0.402	1.047
* fourth SES quintile	-0.193	0.502	-0.412	1.161
* fifth SES quintile	-0.174	0.514	-0.373	1.251
Number of Individuals		1,830		
Number of Obervations		422,730		
LLF		-5,815.555		

*Notes: These models are estimated using the package *clogit* in Stata. The reference facility type is a public hospital. The ratio reported in column (2), which are independent of scale, are formed by dividing preference parameters by the negative of the preference for distance. Ratios can be interpreted as the distance that an individual is willing to travel to aquire one more unit of the given facility attribute. Ratio standard errors are calculated via bootstrap.