CHOOSING A CONTRACEPTIVE PROVIDER:
ACCESS, AWARENESS AND FERTILITY DECISIONS IN URBAN SENEGAL

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ABSTRACT

Rayan Joneydi: Choosing a Contraceptive Provider:
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(Under the direction of David K. Guilkey and Clement J. E. Joubert)

Contraceptive use is low in most parts of Sub-Saharan Africa, contributing to high fertility rates and sustained population growth in this region. As a result, there is growing emphasis on promoting family planning and improving access to contraceptives through various measures. I incorporate the most common types of interventions—implementing an awareness campaign, reducing contraceptive prices, and increasing the quantity and quality of providers—into a dynamic fertility model to compare the effectiveness of these interventions. The model includes the decisions of married women to be sexually active, to use birth control and to select a contraceptive provider among all the providers located within a given distance of their dwelling place. I estimate the model on a rich data set that includes all the contraceptive providers in three cities of Senegal, linked to a longitudinal sample of women. Simulations indicate that price reductions and quality improvements could increase contraceptive use in urban Senegal. However, travel costs and cultural barriers, including the fear of contraceptives and personal opposition, are greater obstacles towards using contraceptives. I find that contraceptive use increased significantly between 2011 and 2015 in the three cities, driven by a large-scale awareness campaign that addressed the benefits of family planning, its acceptance by religious leaders, and widespread misconceptions about the harmfulness of contraceptives.

Amelia, you showed me what it truly means to be a supportive, caring and selfless spouse over the past six years. I am forever grateful.

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SECTION 1
INTRODUCTION

Fertility rates remain high in Sub-Saharan Africa, with an average of five children per women (twice the world average) and a population growth rate of 2.74% in 2016.[1] High fertility rates are associated with a number of adverse effects in this region, including elevated risks of maternal and infant mortality, land degradation and food insecurity (World Health Organization 2005, Cleland et al. 2006). As a result, family planning is rising in the list of development priorities in Sub-Saharan Africa and is a growing recipient of donor funds (Starbird, Norton and Marcus 2016).

In this context, the Gates Foundation launched the Urban Reproductive Health Initiative, a series of large-scale interventions to promote contraceptive use and urban reproductive health in Senegal, Nigeria, Kenya and India. The Senegal branch, named ISSU (Initiative Sénégalaise de Santé Urbaine), implemented two types of interventions in the cities of Dakar, Mbour and Kaolack between 2011 and 2015.[2] Supply-side interventions aimed at improving the quality of public providers by reducing contraceptive stockouts and offering additional training in family planning. Demand-side interventions employed mass media and community outreach to address the benefits of family planning, its acceptance by religious leaders, and misconceptions about the harmfulness of contraceptives.

These interventions were carried out at a large scale in Dakar, Mbour and Kaolack: 92.8% of public health facilities received the supply-side interventions, and 85.4% of married women were exposed to at least one of the media or community programs by 2015. In addition, the Monitoring, Learning and Evaluation (MLE) project, a collaboration between the Gates Foundation and the Carolina Population Center, collected data in these three cities between 2011 and 2015 in order to monitor changes in the supply environment (price, quantity and quality of contraceptive providers) and changes in the percentage of contraceptive users. This unique setting allows me to incorporate the most common types of family planning interventions—

[1] The population of Sub-Saharan Africa grew at an average annual rate of 2.73% between 1960 and 2016, resulting in a doubling of the population approximately every twenty-six years (World Bank Open Data).

[2] In this article, I refer to Dakar as the department of Dakar and its immediate suburbs Guédiawaye, Pikine and Mbao.

implementing an awareness campaign, reducing contraceptive prices, and increasing the quantity and quality of providers—into a fertility model to compare the effectiveness of these interventions.

The agents in my model are married women living in urban Senegal. At each age, a woman can decide to be sexually active and whether or not to use birth control, from the time she gets married until menopause.[3] If she opts for birth control, she selects a contraceptive provider based on price, quality and distance among all the providers that are located within a given distance of her dwelling place. She then becomes pregnant with a probability that depends on her reproductive and provider choices. In particular, selecting a high quality provider may increase the effectiveness of birth control and therefore reduce the probability of pregnancy. The model is dynamic and agents are assumed to be forward looking. In each period of the model, agents take into account the current cost of pregnancy as well as the value of having a child in the next period when making their reproductive and provider choices.

In addition, women may be exposed to four community programs implemented by the ISSU awareness campaign: home visits, community conversations, neighborhood groups and religious talks.[4] I allow for these programs to permanently shift a woman's contraceptive preferences. Furthermore, I incorporate permanent unobserved heterogeneity into the model to control for the endogenous exposure to family planning programs and the endogenous access to providers.

I estimate the model on a uniquely detailed data set from the MLE project. The project collected longitudinal reproductive data from a representative sample of women in Dakar, Mbour and Kaolack between 2011 and 2015. In addition, a list of all pharmacies and facilities offering contraceptives was established in each city and data were collected on the quality of care via audits, staff interviews and client exit interviews. The location of both women and providers were recorded by GPS, and the two samples were linked: we asked contraceptive users to provide the address of the health facility or pharmacy from which they obtained their contraceptive, which was matched with the addresses in our provider sample. This remarkable feature of the data makes it possible to model the choice of providers over the universe of contraceptive providers in each city.

I solve the model using backwards recursion and estimate the structural parameters by maximum likelihood. The estimated model is used to carry out several policy experiments and simulation exercises.

[3]Birth control refers to modern contraceptive methods in this article (less than 3% of married women used traditional methods in the data).

[4]The campaign also included radio programs and television programs, but my reduced-form analyses shows that the their impact was not significant (see section 5).

I start by decomposing into three different factors the increase in contraceptive use that occurred between baseline (2011) and endline (2015) in the matched sample of women (i.e. those who are observed in both waves). During this four year period, (1) women progressed along their life cycle, aging and having children; (2) the supply environment changed, with an overall increase in provider quality, a decline in contraceptive prices, and an increase in the number of providers; (3) ISSU carried out its awareness campaign. Results shows that contraceptive use increased from 25.8% in 2011 to 39.4% in 2015, and that 3.2% of this increase can be explained by aging, 38.1% by changes in the supply environment, and 58.7% by the awareness campaign.

Next, I investigate which type of policies could increase contraceptive use in the present environment, given that a general improvement in quality has already occurred and that many women have already been exposed to the awareness campaign.[5] I find that offering contraceptives for free or raising provider quality to the maximum would have a moderate impact, increasing the percentage of contraceptive users from 34.1% to 37.5% and 38.0%, respectively.[6] On the other hand, entirely eliminating travel costs or exposing women to all four community programs would have a substantial impact, increasing contraceptive use to 49.0% and 62.2% of married women, respectively.

These simulations suggest that further price reductions and quality improvements would increase contraceptive use in urban Senegal, but the price and quality of services are not, at their current level, the main obstacles that prevent women from using contraceptives. Travel costs and cultural barriers, including the fear of contraceptives and personal opposition, are greater obstacles towards using contraceptives. These results are consistent with my descriptive analysis of the data, which indicates that a large share of married women have misconceptions regarding the harmfulness of contraceptives and the majority travel by foot to to see their contraceptive providers.

My paper makes several methodological contributions to the existing literature on the supply-side determinants of contraceptive use. As discussed in the next section, the common approach in this literature is to aggregate provider quality variables at the cluster level and use this as a independent variable in static models of contraceptive use. However, this approach may not capture well the quality of care that is received,

[5]These simulations are conducted on a representative sample of women rather than the matched sample (see section 8 for more details).

[6]The average annual cost of using contraceptives was already low at 4900 CFA (about 10 dollars) in 2015. Quality is measured with an index from 0 to 1 and it was equal to 0.701 on average in 2015 (see section 4.4). Hence, raising the index to the maximum is equivalent to increasing the average quality of services by 42.7%.

as households often bypass the lowest quality providers to obtain better care (Klemick, Leonard and Masatu 2009). I take a novel approach by explicitly modeling the choice of providers, capturing the relative influence of each provider on the reproductive outcomes of women.

My paper is also part of a larger literature on the quality of health services in low-income countries. In recent years, much progress has been made in measuring the quality of care (Leonard and Masatu 2007, Das, Hammer and Leonard 2008, Das et al. 2012) and evaluating policies to improve quality (Björkman and Svensson 2009, Gertler and Vermeersch 2013, de Walque et al. 2015). But the relationship among quality, provider choice, and individual outcomes remains less well understood. I am aware of only two other papers that model the choice of health providers (Klemick, Leonard and Masatu 2009, Cronin, Guilkey and Speizer 2016*b*). These papers analyze the choice of providers using a cross-sectional sample of patients in rural Tanzania and Senegal, respectively. The authors find that households are sensitive to travel costs, but typically bypass the nearest provider to obtain better care. The goal of these studies is to investigate the determinants of provider choices conditional on being a user. I make a contribution to this literature by analyzing how price, quality and distance affect the decision to use services or not, the choice of providers, and reproductive outcomes subsequently.

Finally, my paper is related to a structural literature on the fertility decisions of women (Keane and Wolpin 2007, Keane and Wolpin 2010, Shapira 2013). The majority of the papers in this literature treat pregnancies as a decision rather than an outcome, therefore assuming perfect control over one's fertility. A few papers explicitly model sexual activity and contraceptive use (Hotz and Miller 1993, Arcidiacono, Khwaja and Ouyang 2012, Amador 2015, Forsstrom 2017), but these models do not incorporate the choice of contraceptive providers. Contraceptive prices are typically excluded from the analysis, or in the case of Amador (2015), an average price is used for all women. To my knowledge, this is the first paper to incorporate the supply of contraceptives into a dynamic model of fertility and to model the choice of contraceptive providers.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the structural model. Section 4 describes the context of Senegal and the MLE data. Section 5 provides reduced-form evidence on the impact of the program. Section 6 discusses estimation and identification. Section 6 7 presents the estimation results and the model fit. Section 8 presents the policy experiments. Section 8 concludes.

SECTION 2
RELATED LITERATURE

2.1. Access to Quality and Contraceptive Use

This paper is part of a larger literature that evaluates the role of the health care environment on the contraceptive use and fertility of women in developing countries. For example, Angeles, Guilkey and Mroz (1998) look at the effect of introducing a family planning provider within 30 km of a village on women's probability of giving birth in rural Tanzania. The authors make a contribution to the literature by explicitly modeling the placement of health services: they estimate the probability of having a hospital, a health center, and a dispensary near the village at time t based on observable community characteristics (e.g. population size, child mortality rate) as well as unobservable community types. The probability of conceiving in each year and the three placement equations are jointly estimated, with unobservable types correlated across the set of equations. Results show that failing to account for the endogenous access to services biases the estimates. For example, a simple logit model suggests that having a hospital within 5 km of a village significantly reduces fertility. However, the effect becomes insignificant when placement is modeled, implying that areas with hospitals had low fertility due to unobservables factors. The authors apply the same approach to rural communities in Peru (Angeles, Guilkey and Mroz 2005) and find that, in this setting, the placement of family planning programs can be treated as an exogenous determinant of fertility. Their research shows that the direction and the magnitude of the placement bias depends on the setting as well as the type of facility considered.

In contrast, most papers that evaluate the effect of provider quality on contraceptive use do not address the issue of endogenous access (Feyisetan and Ainsworth 1996, Mensch, Arends-Kuenning and Jain 1996, Ali 2001, Hong, Montana and Mishra 2006, Arends-Kuenning and Kessy 2007, Yao, Murray and Agadjanian 2013). The approach commonly taken in the literature is to estimate a logit of the form $P(C_{ij} = 1) = \text{Logit}(\alpha_0 + \alpha_1 X_{ij} + \alpha_2 Q_j + \alpha_3 Z_j + \varepsilon_{ij})$, where C_{ij} is a dummy variable that is equal to one if woman i in cluster j is using a modern contraceptive method, X_{ij} is a vector of demographic variables (mainly her age, education, number of children, wealth, marital status and religion), Q_j is a vector of provider quality variables aggregated at the cluster level, and Z_j is a limited number of community controls (e.g. the average literacy rate or the availability of pipped water in the cluster). α_2 is the main coefficient of interest in this model: it captures a reduced-form effect of provider quality on contraceptive use if $\mathrm{E}[Q_j \varepsilon_{ij}] = 0$. However, there could be a correlation between access to quality and the unobserved determinants of contraceptive use for many reasons, including the endogenous placement of providers, selective migration or the targeting of quality improvement programs.

Another limitation of the existing literature is that the choice of provider is not modeled. Quality variables are first defined for each provider, then aggregated in some way at the cluster level to proxy the quality of the health care environment (Q_j). Some papers simply take the quality of the nearest provider in each cluster (Feyisetan and Ainsworth 1996, Hong, Montana and Mishra 2006). Others combine the quality of the nearest provider of each type (e.g. the nearest hospital, clinic and dispensary) in varying ways (Mensch, Arends-Kuenning and Jain 1996, Ali 2001, Arends-Kuenning and Kessy 2007). But Klemick, Leonard and Masatu (2009) show that households often bypass the nearest provider to improve the care that they receive. Their study was conducted in Arusha, a rural region of Tanzania that has few clinicians, sparse rural road networks and low population densities, similar to many regions in Sub-Saharan Africa.

Another aggregation method is to average the quality of all providers within a given distance of a cluster (Cronin, Guilkey and Speizer 2016*a*). But variation in distance within this buffer area are not taken into account, and low quality providers necessarily reduce the cluster average, even if women are less likely to choose them. Yao, Murray and Agadjanian (2013) go one step further by taking a weighted average of provider variables within a given radius, where weights are the inverse of distance to capture the fact that farther providers are less likely to be visited. But a cluster with several low quality providers nearby and a few good providers (possibly attracting many contraceptive users) will still be assigned a low quality score. In addition, the weight assigned to each facility is a function of distance only and the distance decay function is arbitrarily chosen.[1]

Conceptually, a woman's reproductive or health outcomes are affected by the presence of a health facility to the extent that she is likely to visit it (aside from externalities or other indirect effects). Thus, the probability of choosing a facility must be correctly modeled to determine its impact on the individual. Rather than

[1] In the general case of Inverse Distance Weighting, the weight assigned to facility f is $w_f = 1/d_f^k$, where d_f is the distance to f and $k \in \mathbb{R}^+$. A special case is $k = 0$ (Cronin, Guilkey and Speizer 2016*a*) and $k = 1$ (Yao, Murray and Agadjanian 2013).

explicitly modeling the choice of providers, the existing literature relies on simplifying assumptions that could bias results.[2] This paper takes a novel approach by explicitly modeling the choice of providers, along with contraceptive use and sexual activity. Intuitively, when deciding to use modern contraceptives, a woman takes into account individual factors as well as the quality and cost associated with each provider. The quality of a provider affects the satisfaction she derives from a visit and how effectively she uses her contraceptive method. Thus, improving provider quality raises the option value of using contraceptives, and providers that are higher in her choice list are more likely to affect her reproductive outcomes.

2.2. Quality of Care Framework

Bruce (1990) developed a framework to evaluate the quality of family planning services that is a standard in the field of family planning. It includes six aspect of services that are essential to clients: choice of methods, information given to users, technical competence, interpersonal qualities, continuity mechanisms and appropriate constellation of services.

Choice of methods refers to the variety of methods that are offered on a reliable basis by the provider. It is an essential aspect of services because reproductive needs vary along the life cycle (e.g. from wishing to delay childbearing, to spacing births, then terminating childbearing) and side effects vary by method. The second aspect of quality is the information given to users (e.g. how to use a given method, possible side effects, etc.), which affects how effectively a client will use her method. Technical competence refers to the knowledge and skills demonstrated by providers and the adherence to best-practice protocols. Interpersonal qualities are "the vehicle by which technical care is implemented and on which its success depends" (Donabedian 1988)—for example, whether the provider demonstrates empathy, honesty, and respect towards clients, seeks to establish a dialogue, encourages questions, and so on. Interpersonal qualities affect the satisfaction derived from seeing a provider, but also the transfer of information and user compliance, and therefore the effectiveness of using contraceptives. Continuity mechanisms are the systems in place to follow up clients after a visit and to ensure the continuity of care, such as follow-up calls, appointments or home visits. Finally, an appropriate constellation of services refers to integrating family planning with other health services to better serve the

[2] For example, the probability of choosing a provider P_f is equal to one if f is the nearest facility and zero otherwise (nearest provider approach), P_f is the same for all facilities within a buffer area and zero beyond (simple average approach), or $P_f = (1/d_f^k)/(\sum_F 1/d_{f'}^k)$ (Inverse Distance Weighting).

reproductive and health needs of women (e.g. by combining family planning with prenatal advice, postnatal care and child health services).

Empirically, these six aspects of services have formed a useful framework to construct quality indicators. For example, choice of methods is typically measured by the number of methods in stock, technical competence by one's training in family planning, and appropriate constellation of services by the number of other Maternal and Child Health (MCH) services offered (Mensch, Arends-Kuenning and Jain 1996, Magnani et al. 1999, Arends-Kuenning and Kessy 2007). Likewise, I use the Bruce framework to define standard quality indicators based on the data available (see section 4.4).

Note that this framework makes the process of defining quality indicators relatively straightforward based on the data available, but the challenge remains upstream to devise survey instruments that accurately capture these six dimensions of quality. For example, Das, Hammer and Leonard (2008) discuss the benefits of using vignettes (case-studies that measure providers' knowledge) and direct observations (attending consultations to evaluate practice) to measure technical competence, rather than using background data (qualifications, years of experience, etc.). These and other survey instruments (such as simulated clients) have their own limitations, but discussing the benefits and shortcomings of each instrument goes beyond the scope of this paper.[3]

[3] I refer the reader to Donabedian (1966) for an early yet outstanding discussion of the complexity of measuring the quality of medical care, and Das, Hammer and Leonard (2008) to appreciate the progress made since then.

SECTION 3
MODEL

3.1. Environment and Choice Set

The agents in the model are married women living in the cities of Dakar, Mbour and Kaolack. A woman makes reproductive decisions annually starting at the age of marriage until she becomes infecund at a fixed age, assumed to be 47.[1] The variables that denote her choices are:

- s_t: sexually active (1) or not (0) at time t
- b_t: using a modern birth control method (1) or not (0) at time t
- f_t: if she opts for birth control, she selects a provider f among all the health facilities and pharmacies that offer a contraceptive method within 5 kilometers of her dwelling place at time t[2]

The agent chooses a combination of s_t, b_t and f_t at the beginning of the period based on her state variables Ω_t. Let $j \in \{1, 2, \ldots, J\}$ denote her choice combination among all the possible choice combinations. To reduce the number of choices, the agent is assumed to use birth control in period t only if she is sexually active during that period. Hence, her options are to be abstinent (option 1), to have unprotected sex (option 2), or to have protected sex (options 3 to J). Having protected sex is associated with selecting a contraceptive provider, therefore the size of the choice set is equal to 2 plus the total number of providers within 5 kilometers.[3]

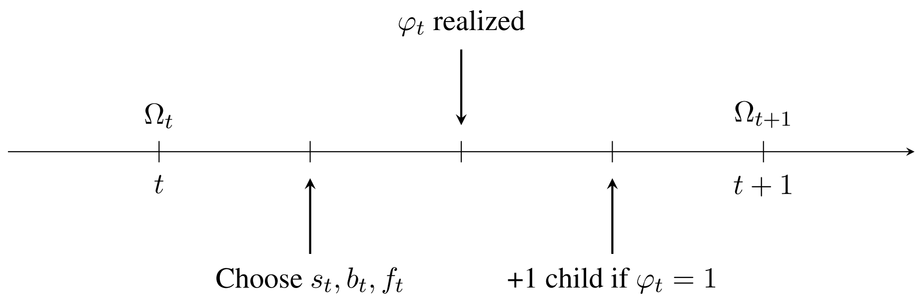
After making her reproductive and provider choices, the agent becomes pregnant ($\varphi_t = 1$) with a probability that depends on her sexual activity, birth control status and other reproductive factors. If a pregnancy occurs, she enters the next period with an additional child.[4] The timing of the model is summarized below:

[1]Sexual activity and contraceptive use are low outside of marriage in Senegal (see section 4.3).

[2]The majority of women choose a provider within 5 kilometers of their dwelling place, therefore I limit the choice set of providers to decrease computation time (see section 4.3).

[3]The size of the choice set varies across women, with a maximum of 89 providers (see section 4.3).

[4]For simplicity, the model assumes that all pregnancies are carried to term. Likewise, the death of a child is a rare occurrence that is not modeled. The under-five mortality rate is 47 per 1000 live births in Senegal and is likely to be lower in urban areas (World Bank Open Data 2015).



3.2. State Variables

The agent observes the following state variables at the beginning of the period, before making her choices:

- t: age
- n_t: number of children
- φ_{t-1}: pregnant (1) or not (0) in the last period
- φ_{t-2}: pregnant (1) or not (0) two periods ago
- p_{ft}: price of pills and injectables at provider f at time t, converted into an annual cost and averaged[5]
- d_{ft}: Euclidean distance from provider f to her dwelling place at time t
- q_{ft}: an index measuring the quality of family planning services provided by provider f at time t (from 0 to 1). This variable is set to 0 for pharmacies.
- h_{ft}: a dummy variable that is equal to 1 if she choses a health facility and 0 otherwise
- ξ_t: number of ISSU community activities ever exposed to at time t, from 0 to 4 (home visits, community conversations, neighborhood groups and religious talks)
- e: level of education, equal to none (0), primary (1) or secondary and above (2)
- e^h: husband's level of education, equal to none (0), primary (1) or secondary and above (2)
- ω: a measure of wealth at baseline, categorized into poorest (0), middle (1), and richeset (2)
- a_k: dummies that indicate whether she got married before the age of 18 ($a_0 = 1$), between 18 and 23 ($a_1 = 1$), or after 23 ($a_2 = 1$)

[5]These are the two most popular methods (see section 4.6).

- χ: the number of good quality health facilities ($q_{ft} > 0.65$) within 2 kilometers of her dwelling place at baseline[6]

- μ: her permanent type, which is known to the woman but unobserved by the econometrician

Note that provider variables (p_{ft}, d_{ft}, and q_{ft}) are taken from the data as given. The agent updates them in each period and makes a no-change forecast when computing the future value of her choices. My assumption is that women do not take into consideration future changes in the supply environment when making their current reproductive decisions.[7]

3.3. Preferences

In each period, the utility associated with choice j and state variable Ω_t is defined by the following function:

$$
\begin{aligned}
u_j(\Omega_t) = \alpha_1 s_t + b_t \Bigg[& \alpha_2 + \sum_{l=1}^{L} \alpha_{3,l} I(\mu = l) + h_{ft}(\alpha_4 + \alpha_5 q_{ft}) \\
& + d_{ft}\Big(\alpha_6 + \sum_{k=1}^{2} \alpha_{7,k} I(\omega = k)\Big) + p_{ft}\Big(\alpha_8 + \sum_{k=1}^{2} \alpha_{9,k} I(\omega = k)\Big) + \alpha_{10}\xi_t \Bigg] \\
& + n_t\Big(\alpha_{11} + \sum_{l=1}^{L} \alpha_{12,l} I(\mu = l) + \sum_{k=1}^{2} \alpha_{13,k} I(e = k) + \sum_{k=1}^{2} \alpha_{14,k} I(e^h = k)\Big) \\
& + n_t^2\Big(\alpha_{15} + \sum_{l=1}^{L} \alpha_{16,l} I(\mu = l) + \sum_{k=1}^{2} \alpha_{17,k} I(e = k) + \sum_{k=1}^{2} \alpha_{18,k} I(e^h = k)\Big) \\
& + \varphi_t\Big(\alpha_{19} + \alpha_{20} t + \alpha_{21}\varphi_{t-1} + \alpha_{22}(1 - \varphi_{t-1})\varphi_{t-2}\Big) \qquad (3.1)
\end{aligned}
$$

α_1 is the marginal utility of having sex. α_2 is the marginal disutility of using contraceptives, which captures the inconvenience of using contraceptives, misconceptions about side effects and personal opposition. This disutility depends on a number of variables, including a woman's unobserved type unobserved type

[6] 29.4% of health facilities have a quality index greater than 0.65 at baseline.

[7] Modeling the evolution of the supply environment (e.g. in a general equilibrium setting, with women's choices affecting the price and quality of services) would be computationally burdensome and would not change the agent's optimization problem in this case. The main advantage would be to conduct more sophisticated policy simulations. For example, in section 8, I increase the quality of services in 2011 to the maximum and simulate women's choices until the age of menopause. In this experiment, quality is increased and maintained at the same level over time. With a general equilibrium model, one could simulate a one period increase in quality and let the system evolve. Quality might deteriorate over time as a result of an increase in demand, which would mitigate the initial increase in contraceptive use.

$\mu \in \{1, 2, \ldots, L\}$ and the quality of her provider q_{ft}. Note that q_{ft} is interacted with h_{ft}, since the quality index is only defined for health facilities. In addition, women take into account the cost of traveling to a provider and contraceptive prices.[8] The effects of both distance and price depend on a woman's wealth level ω. I also allow for family planning awareness programs to permanently shift a woman's contraceptive preferences (α_{10}).

Fertility preferences are captured by the parameters α_{11} through α_{18}. The quadratic specification allows for the utility function to increase as a woman starts having children, then decrease if n_t exceeds her ideal number of children. n_t and n_t^2 are interacted with e, since education may affect the taste for children and the opportunity cost of raising children. Fertility preferences also depend on a woman's type and the level of education of her husband e^h.

Finally, a woman incurs a cost of pregnancy if she becomes pregnant ($\varphi_t = 1$). The cost of pregnancy may increase with age t and if her last pregnancy was one period ago ($\varphi_{t-1} = 1$) or two periods ago ($(1 - \varphi_{t-1})\varphi_{t-2} = 1$). Hence, α_{21} and α_{22} capture birth spacing preferences.

The basic mechanisms of the model are enshrined in the utility function: women tend to have unprotected sex at the beginning of their marriage because the marginal utility of having sex is positive, as well as the marginal utility of having their first child.[9] After giving birth, a woman may wish to delay her next pregnancy to avoid closely spaced births or to limit her family size. Abstinence provides perfect protection, but she must forgo α_1 in this case. Alternatively, she could use birth control to reduce the probability of pregnancy, but there is a utility cost associated with contraceptives. The decision to use birth control or not will partly depend on the quality of available providers, as well as the price she must pay and the distance she must travel to obtain contraceptives.

3.4. Program Exposure

Women can be exposed to up to four family planning programs at midterm (2011) and endline (2015). These interventions were not randomized, thus ξ_t could be correlated with the unobserved determinants of fertility and contraceptive preferences. I control for this endogenous relationship by allowing for μ to shift fertility and contraceptive preferences in the utility function, and also to affect exposure as follows:

[8] I do not model a woman's time constraint, thus α_6 captures both transportation and time costs.

[9] Most women do not use contraceptives until their first child is born. Merely 2.6% of women with no children use contraceptives at baseline.

$$
\xi_t = \beta_0 + \sum_{l=1}^{L} \beta_{1,l} I(\mu = l) + \beta_2 I(y = 2015) + \sum_{k=1}^{2} \beta_{3,k} I(e = k) \\
+ \sum_{k=1}^{2} \beta_{4,k} I(\omega = k) + \beta_5 t + \varepsilon_t \tag{3.2}
$$

where $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$. β_2 captures the additional exposure at endline, compared to midterm. This equation is not estimated at baseline, since ISSU programs were not implemented yet.

3.5. Pregnancies

Denote $P_j(\Omega_t)$ the probability of becoming pregnant in period t as a function of choice j and state variables Ω_t. $P_j(\Omega_t)$ is modeled according to the following logit specification:

$$
\ln \left[\frac{P(\varphi_t = 1)}{P(\varphi_t = 0)} \right] = \begin{cases} 0 \quad \text{if } s_t = 0 \text{ or } t \geq 47 \\ \gamma_0 + \sum_{l=1}^{L} \gamma_{1,l} I(\mu = l) + \gamma_2 t + \gamma_3 t^2 + \gamma_4 \varphi_{t-1} + \gamma_5 b_t \quad \text{if} \\ \qquad\qquad s_t = 1 \text{ and } t < 47 \end{cases} \tag{3.3}
$$

The probability of pregnancy is equal to zero if a woman abstains from having sex or reaches the age of 47. Otherwise, the probability of pregnancy is a function of age to capture the decline in fecundity towards the end of the reproductive life cycle. In addition, women who were pregnant in the last period ($\varphi_{t-1} = 1$) are less likely to become pregnant due to breastfeeding. Using birth control ($b_t = 1$) also reduces the probability of pregnancy. Finally, γ_1 captures permanent unobserved heterogeneity in fecundity.

3.6. Initial Conditions and Types

Agents are assumed to start their reproductive life once they get married because there is little sexual activity and contraceptive use outside of marriage in Senegal (see section 4.3). The initial number of children in the model is therefore zero. The other initial conditions in the model are a woman's level of education e, her husband's level of education e^h, her baseline wealth level ω, and her age of marriage category a_k. These variables, as well as a woman's access to quality at baseline χ, may be correlated with the unobserved determinants of contraceptive use and fertility. For example, women with stronger fertility preferences may choose to get married younger. I control for this endogenous relationship by allowing for the age of marriage to determine her unobserved type, which shifts her fertility and contraceptive preferences in the utility function. Denote $P(\mu = l)$ the probability that the agent is type $l \in \{0, 1, \ldots, L\}$. Type probabilities are modeled according to a multinomial logit specification (Heckman and Singer 1984, Shen 2009, Keane and Wolpin 2010), where the coefficients for type zero are normalized to zero:

$$\ln\left[\frac{P(\mu = l)}{P(\mu = 0)}\right] = \tau_0^l + \sum_{k=1}^{2} \tau_{1,k}^l I(e = k) + \sum_{k=1}^{2} \tau_{2,k}^l I(e^h = k) + \sum_{k=1}^{2} \tau_{3,k}^l I(\omega = k)$$
$$+ \sum_{k=1}^{2} \tau_{4,k}^l a_k + \tau_5^l \chi \tag{3.4}$$

3.7. The Optimization Problem

The agent is forward-looking and assumed to maximize, at each age, the present value of her expected lifetime utility from that age onward. The optimization problem can be defined recursively in a dynamic programming framework. Conditional on her type μ, a woman in state Ω_t will chose the choice combination j that gives her the highest utility $v_j(\Omega_t|\mu) + \varepsilon_{jt}$, where ε_{jt} is a Generalized Extreme Value (GEV) preference shock and $v_j(\Omega_t|\mu)$ is the choice-specific value function:

$$v_j(\Omega_t|\mu) = P_j(\Omega_t|\mu)\Big[u_j(\Omega_t|\mu, \varphi_t = 1) + \delta V(\Omega_{t+1}|\Omega_t, \mu, \varphi_t = 1)\Big]$$
$$+ (1 - P_j(\Omega_t|\mu))\Big[u_j(\Omega_t|\mu, \varphi_t = 0) + \delta V(\Omega_{t+1}|\Omega_t, \mu, \varphi_t = 0)\Big] \tag{3.5}$$

$u_j(\Omega_t|\mu)$ is the per-period utility of choice j, $P_j(\Omega_t|\mu)$ is the probability of pregnancy conditional on choice j and type μ, δ is the discount factor, and $V(\Omega_{t+1}|\mu)$ is the future value function, which is the expected value of the best option in the next state:

$$V(\Omega_{t+1}|\mu) = \mathrm{E}\max_j \Big[v_j(\Omega_{t+1}|\mu) + \epsilon_{jt+1}\Big] \tag{3.6}$$

Equation 3.5 shows that the value of choice j is the sum of two terms. The first term is the probability of becoming pregnant conditional on j times the value of becoming pregnant, which is equal to the current utility

$u_j(\Omega_t|\mu, \varphi_t = 1)$ plus the discounted expected value of having a child in the next period $\delta V(\Omega_{t+1}|\Omega_t, \mu, \varphi_t = 1)$. The second term is the probability of avoiding a pregnancy conditional on j times the value of not becoming pregnant, which is equal to the current utility $u_j(\Omega_t|\mu, \varphi_t = 0)$ plus the discounted expected value of having the same number of children in the next period $\delta V(\Omega_{t+1}|\Omega_t, \mu, \varphi_t = 0)$.

Denote $p_j(\Omega_t|\mu)$ the probability of choosing j conditional on state Ω_t and type μ. I assume a nested logit error structure, which provides the following closed-form solution for the conditional choice probabilities:

$$p_j(\Omega_t|\mu) = \frac{e^{v_j(\Omega_t|\mu)}}{e^{v_1(\Omega_t|\mu)} + e^{v_2(\Omega_t|\mu)} + \left(\sum_{j=3}^{J} e^{v_j(\Omega_t|\mu)/\rho}\right)^{\rho}} \quad \text{for } j \in \{1, 2\}$$

$$p_j(\Omega_t|\mu) = \frac{e^{v_j(\Omega_t|\mu)/\rho}\left(\sum_{j=3}^{J} e^{v_j(\Omega_t|\mu)/\rho}\right)^{\rho-1}}{e^{v_1(\Omega_t|\mu)} + e^{v_2(\Omega_t|\mu)} + \left(\sum_{j=3}^{J} e^{v_j(\Omega_t|\mu)/\rho}\right)^{\rho}} \quad \text{for } j \in \{3, \ldots, J\} \tag{3.7}$$

where $1 - \rho$ is a measure of correlation among the provider nest. The introduction of permanent unobserved heterogeneity in the model relaxes the IIA assumption and captures the permanent correlation across choices, program exposure and pregnancies. In addition, the nested logit errors capture the per-period correlation among provider choices.[10] A small ρ implies that women compare the value of the best providers ($j \in \{3, \ldots, J\}$) to the value of abstinence ($j = 1$) and unprotected sex ($j = 2$).[11]

The GEV distributional assumption also provides a closed-form solution for the future value function:

$$V_j(\Omega_{t+1}|\mu) = \ln\left(\sum_J e^{e^{v_1(\Omega_{t+1}|\mu)} + e^{v_2(\Omega_{t+1}|\mu)} + \left(\sum_{j=3}^{J} e^{v_j(\Omega_{t+1}|\mu)/\rho}\right)^{\rho}}\right) + \gamma \tag{3.8}$$

where γ is Euler's constant. The solution to the optimization problem can be regarded as solving v_j for all choices and possible future states. I close the model by assuming that women die at the age of 70—the life expectancy of women in urban Senegal (2013 Senegal Census Data)—and setting the future value equal to

[10] I do not further decompose the provider nest into sub-nests (e.g. dispensary, clinic and hospital, or public versus private) because I assume that price, distance, and quality are the fundamental variables that determine provider choices in this context. Households in Senegal generally do not have health insurance.

[11] For ρ close to zero, $\left(\sum_{j=3}^{J} e^{v_j(\Omega_t|\mu)/\rho}\right)^{\rho}$ is approximately equal to exponential of the value of the best provider.

zero in the terminal period. The solution method proceeds by backwards recursion starting at $T = 70$.[12] Equation 3.5 provides a scalar value for all $v_j(\Omega_T)$ since $V(\Omega_{T+1})$ is equal to zero. It is then possible to compute $V(\Omega_T)$ for all states in period T using equation 3.8. Given $V(\Omega_T)$, I can compute all $v_j(\Omega_{T-1})$ in period $T-1$ with equation 3.5, and so forth the model is solved recursively back to the first period. Equation 3.7 provides the formula to compute the conditional choice probabilities once the model is solved.

[12] From age 47 to 70 the number of children is fixed and the only choices are to be sexually active or not.

SECTION 4
DATA

4.1. Country Overview

Senegal is a francophone country in West Africa with a high fertility rate (4.8 children per women on average, World Bank Open Data 2016). The population has grown from three million in 1960 to fifteen million in 2016, with an average annual growth rate of 2.84% during this period (see appendix figure 9.1). The country has a stable political environment, marked by the peaceful transition of power since gaining its independence from France in 1960. Nearly half of the population is living in urban areas and a quarter in the region of Dakar, the capital (2013 Census). Senegal is part of the Sahel region, a belt to the south of the Sahara with a semi-arid climate and a predominantly muslim culture.[1] The study of contraceptive use and fertility in this region is of particular interest since Sahelian countries—including Senegal, Mauritania, Mali, Niger, Chad, Sudan and Eritrea—are among the countries with the highest fertility rates in the world.

4.2. The MLE Project

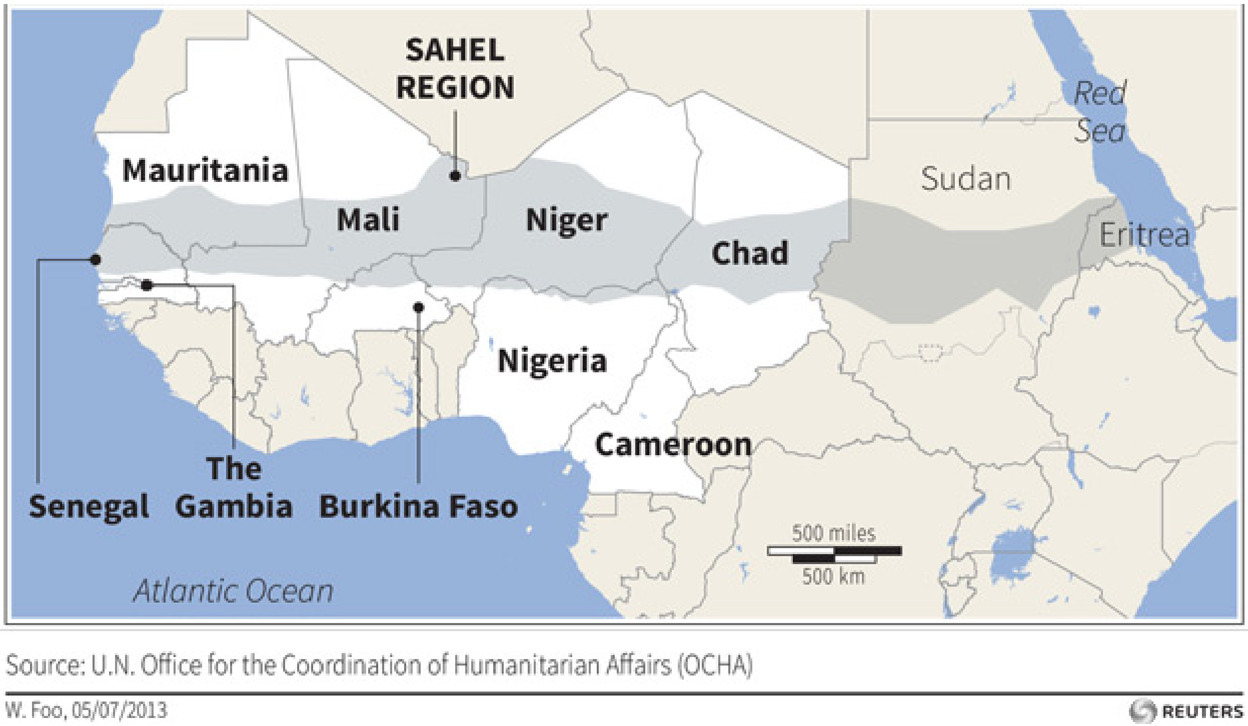
The Monitoring, Learning and Evaluation (MLE) project collected data from women living in three cities in Senegal: Dakar, Mbour and Kaolack. The region of Dakar is the largest urban area in Senegal, with a total population of 3.1 million inhabitants (2013 Census). The survey in Dakar covered the inner city and the neighboring suburbs of Guédiawaye, Pikine and Mbao. Mbour and Kaolack are secondary cities that have approximately half a million inhabitants.

A multi-stage stratified sampling design was used to obtain a sample of women that was representative of each city at baseline (2011).[2] Women were then tracked and interviewed at endline (2015), with an

[1] 96.1% of the population in Senegal is muslim (EDS-Continue 2015).

[2] The primary sampling units (clusters) were first divided into poor and non-poor based on the overall characteristics of the cluster (types of houses, access to pipped water, etc.). An equal number of poor and non-poor clusters were then selected in each city with a probability that was proportional to the size of each cluster. The urban poor were oversampled as a result. All the statistics provided in this paper are unweighted.

Figure 4.1: Sahel Region



additional sub-sample interviewed at midterm (2013) in Guédiawaye, Pikine and Mbao. In each survey round, information was collected on fertility preferences, reproductive behavior, the choice of contraceptive providers, and the history of births. In Dakar, data was also collected from a representative sample of men in 2011 and 2015 to learn about their fertility preferences and their attitude towards family planning. These two samples are cross-sectional and smaller than the women's sample, with 2270 men interviewed in 2011 and 2214 men interviewed in 2015.

In addition, a list of all pharmacies and health facilities offering reproductive health services was established in each city based on official registries and field investigation. They were audited in 2011 and 2015 to gather information on MCH services, contraceptive prices, management practices and staff qualification. In each health facility, up to four staff members involved in the delivery of reproductive health services were randomly selected and interviewed. Questions were asked regarding their qualifications, knowledge of family planning, and practices during family planning consultations. The major health facilities in each city—those who had a high-volume of activity, were well staffed and offered a wide range of methods—were also subject to client exit interviews. Fifty women were selected in each high-volume facility to collect information on their experience after their reproductive health visit. Finally, women were linked to their contraceptive providers. Women who were using a modern method at the time of the survey reported the address of the health facility or pharmacy from which they last obtained their contraceptive. These addresses were then matched to the providers in our master list.

The purpose of the MLE project was to collect data to monitor and evaluate the ISSU project, which implemented supply-side and demand-side interventions between 2011 and 2015 in the three cities. All interventions started after the baseline data was collected. The supply-side interventions focused on training family planning providers in the public sector and implementing the Informed Push Model (IPM) to reduce stockouts. The IPM is a centralized distribution system where trained logisticians are responsible for contacting providers and re-supplying them in contraceptives on a regular basis.[3] The demand-side interventions raised awareness of the benefits of family planning, discussed the acceptance of family planning by religious leaders, and addressed misconceptions about the harmfulness of contraceptives. The media component of the intervention included radio and television programs, and the community component included home visits, community conversations, neighborhood groups and religious talks.

All interventions ended in 2015, except for the IPM system, which was extended to the rest of the country after 2015. The interventions were well funded by the Gates Foundation and carried across the board in the three cities: 92.8% of public health facilities received the supply-side interventions, representing 88.4% of the contraceptive providers chosen by women in 2015. In addition, 85.4% of women in the estimation sample were exposed to at least one of the six media and community programs by 2015, and 40.2% of were exposed to at least one of the four community programs by 2015.

4.3. Sample Selection

The baseline sample includes 9614 women between the ages of 15 and 49, of which 6927 were successfully interviewed at endline.[4] The sample selection process is described in table 4.1 and starts with all 9614 women. At each step, I delete all person-year observations that do not meet the selection criterion. For example, if a woman is single at baseline and midterm but married at endline, I keep her endline observation.

[3](Daff et al., 2014) describe in detail the IPM and how it resolved issues with the previous "pull-based" system, which relied on providers traveling to a local warehouse and using their own cash on hand to buy contraceptives.

[4]193 women were not eligible for a follow-up because they were just visiting the household at baseline. Of the 9421 eligible women, 81.46% were tracked in the study sites, 12.9% had moved out of the study sites, 0.8% were deceased and 4.8% were not followed up. The response rate among those who were tracked was 90.27%.

Table 4.1: Sample Selection Process

Reason	Dropped	Remaining
Age inconsistent	25	9589
Age above 46	318	9271
Single	3368	5903
Infecund	96	5807
Uncommon method	6	5801
Missing contraceptive use	5	5796
Abstinent but became pregnant	9	5787
Missing birth history	2	5785
More than 12 children	1	5784
Chose a health facility beyond 5 km	20	5764
No health facilities within 5 km	1	5763
Chose a pharmacy beyond the nearest five	7	5756
Missing age or marriage	49	5707
Married before 10	5	5702
Age of marriage inconsistent	3	5699
Missing age of oldest child	1	5698

25 women are dropped because their age is largely inconsistent across the two waves, and 318 are dropped because they are older than 46 at baseline (the last decision period in the model). There is limited sexual activity and contraceptive use outside of marriage in Senegal (4.5% of single women had sex in the past three months and merely 3.8% used contraceptives in the full baseline sample), therefore I limit the sample to married women. Most contraceptive users choose condoms, pills, injectables, implants or IUDs. A few women selected less common methods (sterilization, emergency contraception, spermicides, etc.) and are excluded from the sample. I also drop a small number of women who selected a health facility beyond 5 kilometers or a pharmacy beyond the nearest five.

Table 4.2: Person-Year Observations

City	Baseline	Midterm	Endline	Total
Dakar	2489	1425	1888	5802
Mbour	1114	–	953	2067
Kaolack	1181	–	936	2117
Total	4784	1425	3777	9986

The final sample is broken-down by city in table 4.2. There are 4784 observations at baseline, 1425 at midterm and 3777 at endline, for a total of 9986 person-year observations. 58.1% of these observations are in Dakar, 20.7% in Mbour and 21.2% in Kaolack.

Table 4.3: Provider Sample

	Baseline Providers		Endline Providers	
City	Health Facilities	Pharmacies	Health Facilities	Pharmacies
Dakar	122	315	182	412
Mbour	13	27	19	27
Kaolack	25	32	27	34
Total	160	374	228	473

Dakar also has the largest number of contraceptive providers, with 122 health facilities and 315 pharmacies at baseline (table 4.3). In total, there are 160 health facilities and 374 pharmacies in the estimation sample at baseline. The number of providers increases over time, with 228 health facilities and 473 pharmacies in the estimation sample at endline. Provider data was not collected at midterm except in the suburbs of

Guédiawaye, Pikine and Mbao, so I apply the endline supply environment to the midterm sample of women. Thus, I allow women to choose from the endline sample of providers in 2013.

The size of the provider choice set varies by city and across women. The average choice set includes 34.7 providers at baseline and 45.5 providers at endline. The largest choice set includes 70 providers at baseline and 89 at endline. Note that there are always five pharmacies in a woman's choice set, thus the largest choice set includes 84 health facilities plus 5 pharmacies.

Table 4.4: Provider Choice Set

	Baseline			Endline		
City	Min	Max	Average	Min	Max	Average
Dakar	8	70	46.2	9	89	65.3
Mbour	18	18	18	13	24	23.8
Kaolack	10	28	26.2	6	31	27.9
Total	8	70	34.7	6	89	45.5

4.4. Model Variables

Table 4.5 provides summary statistics for the permanent characteristics of women in the estimation sample. e is the highest level of education at the age of marriage, categorized into none (0), primary (1), and secondary or more (2). The educational attainment of women is limited and typically doesn't change after marriage, therefore it is treated it as a permanent characteristic of women in the model. 42.6% of women have no education, 36.4% have primary education, and merely 21.0% have secondary or more (I combine secondary and tertiary because only 3.6% of women have tertiary education).

e^h is the husband's level of education, which is defined in the same way as e. A larger share of husbands have no education (47.3%), but those who go to school are more likely to reach the secondary level (32.0%).

ω captures a woman's wealth status at baseline. First, I construct a wealth index by running a principal component analysis on a list of household variables and keeping the first component. These variables capture the living standards of a woman at baseline, such as having finished floors and walls, the number of rooms in her house, having access to electricity and running water, owning a stove, etc. Next, I construct ω by dividing the wealth index into three quantiles (poorest, middle, richest) using the entire sample of households at baseline.

I divide the age of marriage into three categories: before 18, between 18 and 23, and after 23. The majority of women (50.4%) get married between 18 and 23. Finally, χ is equal to the number of health facilities that have a quality index greater than 0.65 and are located less than 2 kilometers from a woman baseline.

Table 4.5 provides summary statistics for the time-varying demographic variables in the estimation sample. A woman is considered sexually active if she had sex in the past three months. 85.2% of women are sexually active and 22.8% are using contraceptives at baseline. By endline, 36.6% of women are using contraceptives.

Table 4.5: Permanent Demographic Characteristics

Variable	Description	Average	Min	Max
$I(e=0)$	No education	0.426	0	1
$I(e=1)$	Primary education	0.364	0	1
$I(e=2)$	Secondary education	0.210	0	1
$I(e^h=0)$	Husb. no education	0.473	0	1
$I(e^h=1)$	Husb. primary education	0.207	0	1
$I(e^h=2)$	Husb. secondary education	0.320	0	1
$I(\omega=0)$	Poorest	0.355	0	1
$I(\omega=1)$	Middle	0.337	0	1
$I(\omega=2)$	Richest	0.308	0	1
a_1	Married before 18	0.260	0	1
a_2	Married between 18-23	0.504	0	1
a_3	Married after 23	0.236	0	1
χ	Baseline access	2.69	0	9

The average number of children increases from 2.98 at baseline to 3.24 at endline. Note that the endline sample includes women who were not married yet at baseline. Thus, the endline number of children is larger if one restricts the data to the matched baseline-endline sample (3.75 on average).

The timing of pregnancies is constructed by dividing the history of births into 12 month intervals. $\varphi_{t-2} = 1$ if a woman gave birth 12 to 23 months before the interview, $\varphi_{t-1} = 1$ if she gave birth 0 to 11 months before the interview, and $\varphi_t = 1$ if a child is born 1 to 12 months after the interview.

ξ_t is the number of ISSU community activities that a woman has been ever exposed to at time t, including home visits, community conversations, neighborhood groups and religious talks. Exposure is equal to zero for all women at baseline. At endline, women have been exposed to 0.684 programs on average; 59.8% have not received any programs, 20.8% have received one, 12.0% have received two, 6.1% have received three, and 1.3% have received all four.

Table 4.6: Time-Varying Demographic Characteristics

Variable	Description	Baseline Average	Midterm Average	Endline Average	Min	Max
t	Age	30.9	32.1	32.7	15	46
s_t	Sexually active	0.852	0.862	0.860	0	1
b_t	Using birth control	0.228	0.354	0.366	0	1
n_t	Number of children	2.98	3.19	3.24	0	12
φ_t	Pregnant in t	0.190	0.158	–	0	1
φ_{t-1}	Pregnant in $t-1$	0.214	0.197	0.168	0	1
φ_{t-2}	Pregnant in $t-2$	0.209	0.180	0.173	0	1
ξ_t	Program exposure	0	0.484	0.684	0	4

Table 4.7 provides summary statistics for the provider variables in the estimation sample. The quality index measures the quality of family planning services offered by health facilities (it is not defined for pharmacies). This index is an average of six quality indicators that are standard in the family planning literature and based on the Bruce framework (see section 2.2). The first indicator is the number of methods (condoms, pills, injectables, implants and IUDs) offered by the health facility at time t. The second is a dummy variable that is equal to one if pills and injectables (the most popular methods) are in stock at time t. The third quality indicator is the percentage of staff members (among those who offer reproductive health services) that do not impose any restrictions on contraceptives at time t. Restrictions include requiring women to have their husbands' consent, to be within a certain age, or to have a minimum number of children in order to receive contraceptives. Together, these first three indicators capture the choice of methods in the Bruce framework. The fourth indicator is the percentage of family planning employees who received a training from ISSU at time t. The fifth indicator is the number of other MCH services that are offered at the health facility, which captures the constellation of services in the Bruce framework.[5] The last indicator is a dummy variable that is equal to one if the health facility has all of the following basic medical material at time t: a

[5]This indicator includes eleven MCH services: prenatal care, delivery, emergency obstetrics, postnatal care, post-abortion care, STI diagnostic and treatment, voluntary counseling and testing, and four types of child health services (vaccination, growth monitoring, respiratory illness and oral re-hydration therapy).

speculum, a tenaculum, a sponge clamp, antiseptics, cotton and gloves. I divide "number of methods" by 5 and "number of other MCH activities" by 11 to have indicators that range from 0 and 1, then I average the six indicators to obtain a quality index.

$p_{f,t}$ captures the average annual cost of obtaining contraceptives from provider f at time t. This variable is based on the price of pills and injectables, which are the most popular methods in urban Senegal (see section 4.6). An injectable shot usually provides protection for 3 months and pills are sold in packs of 28. To obtain an annual cost, I set the price variable equal to $(4 \times \text{price of an injectable shot} + 12 \times \text{price of a pack of pills})/2$. Prices are expressed in thousands of CFA francs (1 dollar equals 500 CFA francs approximately).

Finally, the centroid of clusters and the exact location of providers were recorded by GPS, which allows me to compute the Euclidean distance from a woman's dwelling place to each contraceptive provider.[6] The largest value taken by d_{ft} is 5.88 kilometers.

Table 4.7: Provider Variables

	Baseline Average	Endline Average	Min	Max
Number of methods	4.08	4.55	1	5
Pills or injectables in stock	0.919	0.965	0	1
No restrictions	0.361	0.606	0	1
ISSU trained	0	0.385	0	1
Number of other MCH services	7.88	7.80	2	11
Basic medical material	0.519	0.632	0	1
Quality index ($q_{f,t}$)	0.555	0.701	0.064	0.985
Price ($p_{f,t}$)	4.98	4.90	0	21
Distance ($d_{f,t}$)	2.38	2.50	0.002	5.88

4.5. Provider Choice

It can be seen in table 4.7 that the supply environment has improved between 2011 and 2015: the number of providers increased from 160 to 228, while the price of contraceptives declined slightly and the quality index increased on average. Figure 9.2 in the appendix provides the distribution of prices for public and

[6]Clusters correspond to urban census tracts and cover small areas, typically the size of a neighborhood. Women who subsequently moved from their baseline cluster were tracked and the exact location of their new dwelling place taken by GPS. I refer to the location of a woman as her dwelling place in both cases.

private providers. Public providers were cheaper on average in both waves. In addition, the government passed a decree in 2010 to set the price of contraceptives in the public sector, which resulted in a convergence of prices among public providers by 2015. Table 4.8 indicates that 83.6% of users in 2011 and 92.1% of users in 2015 obtained their method from a public provider. The most common choice is the health post, a relatively small and public health facility.

Table 4.8: Provider Types (%)

	Baseline		Endline	
Type	Available	Chosen	Available	Chosen
Hospital	1.3	8.7	1.4	3.5
Health center	5.8	22.3	3.9	16.5
Health post	16.7	49.8	15.7	66.2
Other public	3.2	2.9	4.9	5.9
Private health facility	3.0	5.9	6.7	1.8
Pharmacy	70.0	10.5	67.5	6.1

Table 4.9 indicates that poorer women are more likely to choose providers that are cheaper and closer. Overall, the data suggests that distance is a significant determinant of provider choices. For example, client exit interviews reveal that 60.8% of women travelled by foot to their reproductive health appointments, 21.4% used public transportation, 13.7% employed taxis, 1.2% used a personal car, and 2.8% used a cart, motorcycle or other form of transportation in 2011.

Nonetheless, the majority of contraceptive users (61.7% in 2011 and 57.7% in 2015) bypass the nearest provider to obtain better care on average. Those who bypass the nearest provider choose a provider that is on average 0.95 km farther, offers 0.11 more methods and 0.56 more MCH services in 2015 (table 4.10). In addition, these providers are more likely to impose no restrictions (+3.9 percentage points) and have a greater share of of ISSU trained staff (+2.9 percentage points).

Table 4.9: Provider Choice by Wealth Status

	Baseline	Endline
Price (1000 CFA)		
Poorest	1.768	1.375
Middle	1.938	1.353
Richest	2.111	1.684
All	1.943	1.460
Distance (km)		
Poorest	0.979	0.836
Middle	1.080	0.944
Richest	1.078	1.032
All	1.048	0.935
Nearest (%)		
Poorest	37.3	47.6
Middle	40.1	40.9
Richest	37.4	38.2
All	38.3	42.3

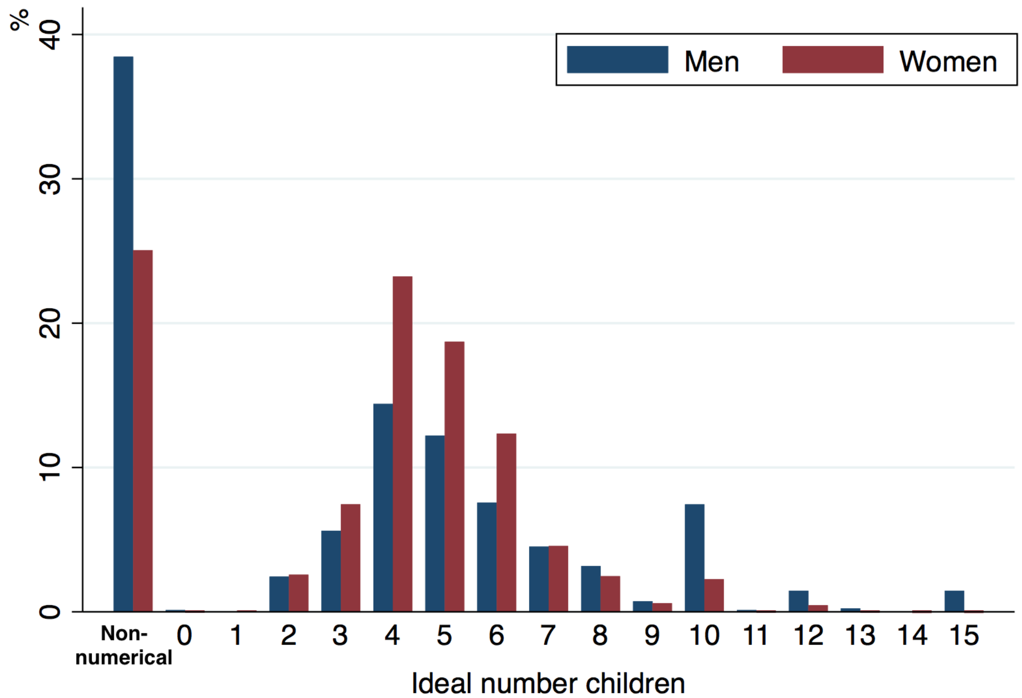
Table 4.10: Nearest vs. Chosen Provider in 2015 (Among Users Who Bypass)

	Nearest	Chosen
Number of methods	3.80	4.47
Pills or injectables in stock	0.948	0.929
No restrictions	0.513	0.526
Recently trained	0.597	0.668
Number of other MCH services	7.84	8.99
Basic medical material	0.587	0.602
Quality index	0.686	0.739
Distance	0.50	1.63

4.6. Reproductive Preferences

Table 4.5 shows that merely 22.8% of married women use contraceptives at baseline (compared to 58% in the United-States, Population Reference Bureau 2015). The most popular methods are injectables (43.6% of users at baseline), followed by pills (36.3%), implants (7.6%), condoms (7.7%) and IUDs (4.8%).

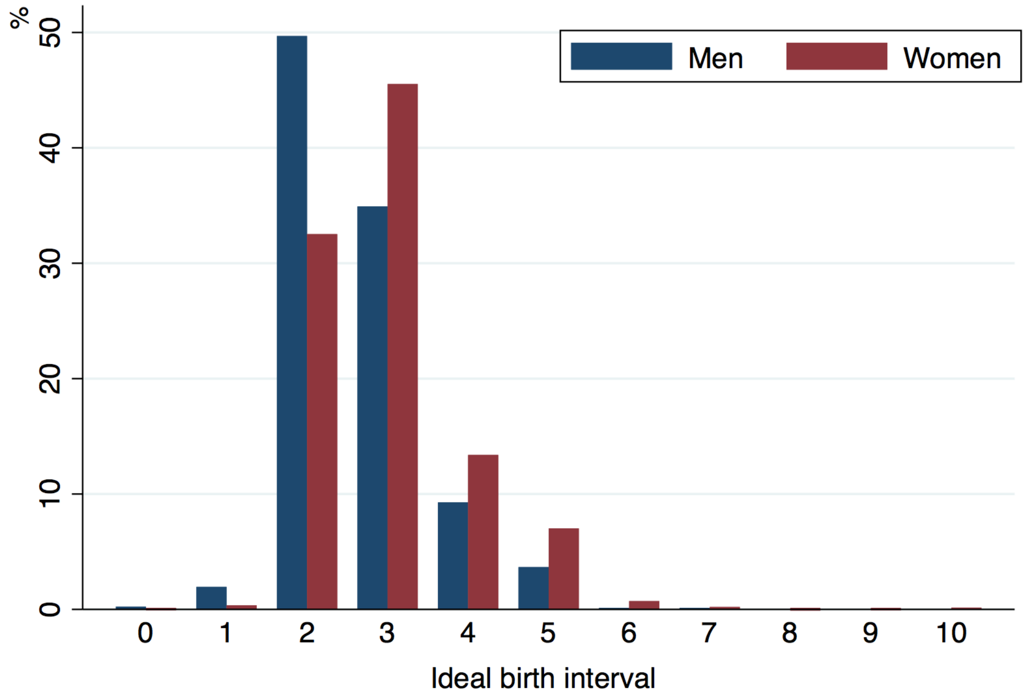
Figure 4.2: Fertility Preferences



Despite the low prevalence of contraceptives, most women desire to limit or space their pregnancies. 61.8% of married women report an ideal number of children between three and six at baseline (figure 7.1). 25.1% provide a non-numerical answer, such as “I do not know”, “I have not thought about it” or “it is up to God”. Among those who provide a numerical answer, the ideal family size is on average 5.0 children. Men tend to have stronger fertility preferences than women. 39.8% of married men report an ideal number of children between three and six at baseline, and 38.5% provide a non-numerical answer. Among those who provide a numerical answer, the ideal number of children is 6.0 on average. In terms of birth spacing, 91.4% of married women and 93.9% of married men prefer to have a two to four year interval between children (figure 4.3). Merely 0.4% of married women and 2.0% of married men want a birth interval shorter than two years.

In addition, 26.1% of married women who are pregnant report that their pregnancy was unwanted when it occurred. Among married women who are not pregnant, 21.2% are sexually active, not using any type of modern contraceptives, but state that it would be an issue if they became pregnant in the coming weeks. The main reasons they provide for not using contraceptives are fear of side effects (24.8%), currently breastfeeding

Figure 4.3: Spacing Preferences



(22.3%), partner's opposition (11.7%), personal opposition (11.2%), health issues (10.7%) and postpartum amenorrhea (10.2%). Note that there are widespread misconceptions about the harmfulness of contraceptives. For example, a significant share of women believe that people who use contraceptives end-up having health issues (57.5%) or that injectables cause irreversible sterility (32.2%) at baseline.

The data suggest that most couples do not discuss their fertility preferences (table 4.11). In addition, 80.6% of women need their husband's consent to use contraceptives. However, the same percentage report that they can convince their husband to use family planning. Note that family planning is generally approved in urban Senegal. For example, 77.8% of married women and 67.8% of married men at baseline agree that couples who practice family planning have a better quality of life than those who do not. Finally, the decision to have children is generally determined by both spouses, and women are the ones primarily decide which contraceptive method to use.

Table 4.11: Communication With Husband and Agency Over Reproductive Decisions at Baseline (%)

	Yes	No	You	Joint	Husb.	Other[1]
Ever talked about number of children with husband	30.1	69.9				
Ever talked about FP with husband	54.8	45.2				
Need husband's consent to use FP	80.6	19.4				
Can convince husband to use FP	79.9	20.1				
Who decides num. of children mainly			24.2	32.1	14.4	29.3
Who chooses the method mainly			51.2	34.1	8.1	6.6

[1] The most common free responses are "It is up to God" and "We have never talked about it".

SECTION 5
REDUCED-FORM ANALYSIS

I employ a fixed-effects model to evaluate the impact of the awareness campaign on contraceptive use and to explore various impact mechanisms. The structural model expresses the decision to use contraceptives as a function of a woman's age, number of children (interacted with education and husband's education), time since last pregnancy, program exposure, the supply environment and several time invariant variables (education, husband's education, baseline wealth status, age of marriage and baseline access to quality). I exclude the supply environment from my reduced-form model and drop the time invariant variables:

$$
\begin{aligned}
b_t = {} & \lambda_0 + \lambda_1 t + \lambda_2 t^2 + n_t\Big(\sum_{k=1}^{2}\lambda_{3,k} I(e=k) + \sum_{k=1}^{2}\lambda_{4,k} I(e^h=k)\Big) \\
& + n_t^2\Big(\sum_{k=1}^{2}\lambda_{5,k} I(e=k) + \sum_{k=1}^{2}\lambda_{6,k} I(e^h=k)\Big) + \lambda_7\varphi_{t-1} + \lambda_8(1-\varphi_{t-1})\varphi_{t-2} \\
& + \lambda_9\xi_t + \nu + \epsilon_t
\end{aligned}
\tag{5.1}
$$

where t is a woman's age, e her level of education, e^h her husband's education, φ_{t-1} her pregnancy status one year ago, φ_{t-2} her pregnancy status two years ago, and ν is an individual fixed-effect. I estimate this model with fixed effects, using the sample of women who have at least two observations (3391 women). This model is relatively simple and static, but it controls for permanent unobserved heterogeneity. Essentially, the model captures the change in contraceptive use that is associated with program exposure by controlling for the baseline level of contraceptive use.

I estimate two versions of equation 5.1. The first model includes the following exposure variables: a dummy that is equal to one if a woman has ever heard any ISSU radio program, a dummy that is equal to one if a woman has ever heard any ISSU television program, and the number of ISSU community program that a woman has every been exposed to from zero to four. I find that the television program did not have a significant impact on contraceptive use (table 5.1). The radio coefficient is positive but not significant at the 10% level (pvalue = 0.18). In contrast, the parameter associated with the community variable is significant at the 1% level and is equal to 0.046, which implies that the probability of using contraceptives increases by 4.6 percentage points with each additional community program that a woman receives. Simulations suggest that exposing all women to the four community activities at endline would increase contraceptive use from 39.4% to 55.6%. In addition, this model fits well the average level of contraceptive use at baseline (25.8%) and endline (39.4%) in the matched sample.

I exclude the radio and television variables in the second model and obtain the same results. Since radio and television do not have a significant impact on the decision to use contraceptives, I only include the community variable in my structural model. This reduces the computation burden of the model—including radio and television would add two more probability of exposure equations, one for each type of program.

Next, I investigate different channels through which community programs can affect the decision to use contraceptives. The awareness campaign included home visits, community conversations, neighborhood groups and religious talks that discussed the benefits of limiting family size, addressed misconceptions about the harmfulness of contraceptives, and discussed the place of family planning in Islam. Table 5.2 shows the impact of the community programs on several dependent variables. The control variables are similar to the previous fixed-effects models. "Misconceptions" is a dummy variable that is equal to one if a woman agrees that people who use contraceptives end up having health issues. Women who were not using any type of birth control method were asked to provide a reason. "Opposition" and "husband opposition" are dummy variables that are equal to one if a woman reported personal opposition and husband opposition, respectively. "Benefits" is equal to one if a woman agrees that couples who practice family planning have a better quality of life than those who do not. "Ideal number" is the total number of children that a woman would like to have ideally (non numerical answers are excluded). Finally, "ideal spacing" is the ideal age interval between two children.

I find that the awareness campaign significantly reduced misconceptions and personal opposition. The campaign also significantly increased awareness about the benefits of family planning. However, it had little or no impact on husbands' opposition and women's fertility preferences. Based on these results, I allow the program to permanently shift the disutility of using contraceptives in my structural model, but not fertility preferences.

Table 5.1: Impact of Different Family Planning Programs

	Model 1	Model 2
Radio	0.030	
	(0.019)	
Television	-0.014	
	(0.017)	
Community	0.050***	0.052***
	(0.010)	(0.096)
Controls	Yes	Yes
Fixed effects	Yes	Yes
R^2	0.0529	0.0529
Model fit		
Data 2011	0.253	0.253
Model 2011	0.264	0.263
Data 2015	0.391	0.391
Model 2015	0.390	0.390
Counterfactual (community=4)		
Model 2015	0.570	0.558
Number of observations	3391	3391

Standard errors are clustered at the cluster level (in parenthesis).
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 5.2: Impact Mechanisms

	Misconceptions	Opposition	Husb. opposition	Benefits	Ideal number	Ideal spacing
Community	-0.023**	-0.021**	-0.006	0.028**	-0.068*	-0.004
	(0.011)	(0.009)	(0.009)	(0.011)	(0.038)	(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.002	0.001	0.002	0.005	0.007	0.004
Model fit						
Data 2011	0.581	0.110	0.086	0.788	5.03	2.98
Model 2011	0.562	0.109	0.086	0.788	5.06	2.99
Data 2015	0.482	0.083	0.078	0.806	5.09	2.95
Model 2015	0.475	0.074	0.076	0.806	5.04	2.94
Counterfactual (community=4)						
Model 2015	0.400	0.004	0.058	0.897	4.82	2.93
Number of observations	3391	2834	2834	3389	3280	3387

Standard errors are clustered at the cluster level (in parenthesis).
***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

SECTION 6
STRUCTURAL ESTIMATION

6.1. Likelihood Function

Given a vector of parameters θ, the likelihood function for woman i conditional on her type μ is:

$$\mathcal{L}_i(\theta|\mu) = \prod_t \prod_j \left(p_j(\Omega_{it}, \theta, \mu) P_j(\Omega_{it}, \theta, \mu)^{\varphi_{it}} (1 - P_j(\Omega_{it}, \theta, \mu))^{(1-\varphi_{it})} \right)^{d_{ijt}}$$

$$\times \phi(\xi_{it}|\Omega_{it}, \theta, \mu)$$

where d_{ijt} is a dummy that is equal to one if individual i chooses j at time t and ϕ is the probability density function of $\xi_{it} \sim \mathcal{N}(0, \sigma^2)$. The likelihood of the observed data is a weighted average of the type-specific likelihood functions, multiplied across individuals:

$$\mathcal{L}(\theta) = \prod_i \sum_{l=0}^{L} P(\mu = l) \mathcal{L}_i(\theta|\mu = k)$$

θ is estimated by maximizing the likelihood function with a Quasi-Newton algorithm. At each iteration, a line search is performed in a direction determined by the negative inverse Hessian times the gradient of $\mathcal{L}$, where the Hessian is approximated using the Broyden, Fletcher, Goldfar, and Shanno (BFGS) method. Standard errors are computed by estimating the asymptotic covariance matrix of the maximum likelihood estimator with the Outer Product of the Gradient (OPG) method.

6.2. Identification

The parameters of the utility function are identified by covariation in sexual activity, contraceptive use and provider choices across the state space. For example, the birth spacing parameters α_{21} and α_{22} are identified by observing women who are otherwise comparable choosing different combinations of choices, depending on how recently they gave birth. The key parameters of interest are α_2 through α_{10}, which capture the effect of the supply environment and family planning programs in the utility function. There are two potential sources of endogeneity that must be addressed in this regard.

First, access to quality might be correlated with the unobserved determinants of contraceptive use for various reasons discussed in section 2.1. To illustrate this point, suppose there are two types of women. Type one is less likely to use contraceptives due to some fixed unobservable characteristics. In addition, type one is more present in underserved areas where provider quality is generally lower. In this case, there is a spurious positive correlation between contraceptive use and access to quality. As discussed in the literature review, the common approach of aggregating quality at the cluster level, controlling for a limited number of community variables, would bias results.

In contrast, my model controls for permanent unobserved differences in the disutility of contraceptives (such as personal opposition) and in fertility preferences (such as a stronger taste for children) with a discrete number of unobserved types. Access to quality determines the unobserved type of a woman, which shifts her fertility and contraceptive preferences in the utility function. This allows for a correlation between access to quality and the unobserved determinants of fertility and contraceptive preferences.

The second issue is that exposure to family planning programs could be correlated with unobserved determinants of fertility and contraceptive preferences. For example, community activities could be targeted towards women who fear contraceptives, or women who have a stronger desire to control their fertility could select into a greater number of programs. The model includes an exposure equation to control for this type of endogenous relationship. Program exposure is a function of both observable characteristics and unobserved types. Thus, the model allows for a correlation between program exposure, fertility preferences and contraceptive preferences through the unobserved types.

SECTION 7
RESULTS

7.1. Parameter Estimates

Table 9.1 (appendix) reports the estimates and standard errors of the parameters in the utility function. The model is fit with three types. Type one women have a larger disutility of using contraceptives (-1.834) than type zero (-1.356) and type two (-1.506) women. As expected, the parameters associated with price (α_6, α_7) and distance (α_8, α_9) are negative and larger for poorer women, while the parameters associated with provider quality (α_5) and family planning programs (α_{10}) are both positive. Note that α_4 is equal to -0.258 and α_5 is equal to 0.738. Thus, between a health facility and an equally distant and priced pharmacy, a woman will prefer the health facility if its quality index is greater than $0.258/0.738 = 0.350$[1]. Parameters α_{11} through α_{18} indicate that type one women have lower fertility preferences compared to type zero and type two women and that education reduces fertility preferences (see figure 7.1). The cost of pregnancy increases with age and if a woman gave birth recently. Finally, ρ is equal to 0.252, indicating that provider choices are correlated, and the discount factor is fixed at 0.9.[2]

Table 9.3 (appendix) reports the estimates and standard errors of the parameters in the pregnancy equation. The probability of pregnancy decreases with age, if a woman gave birth in the last period, and if she uses birth control. In addition, type one and two women are less likely to become pregnant, conditional on being sexually active.

Table 9.2 (appendix) provides the estimates of the exposure equation. Exposure increased significantly in 2015 compared to 2013. Type one women were the most likely to be exposed to the community programs, followed by type zero women. In addition, older women were slightly more likely to receive the intervention (β_5 is significant at the 10% level), but exposure did not vary significantly by education and wealth status.

---

[1] Just 5.0% of health facilities have a quality index below 0.350 at baseline

[2] The discount factor is often not estimated because it requires an exclusion restriction that affects the transition probabilities but not the utility function to properly identify it (Arcidiacono, Sieg and Sloan 2007).

Figure 7.1: Fertility Preferences by Education (Type 1)

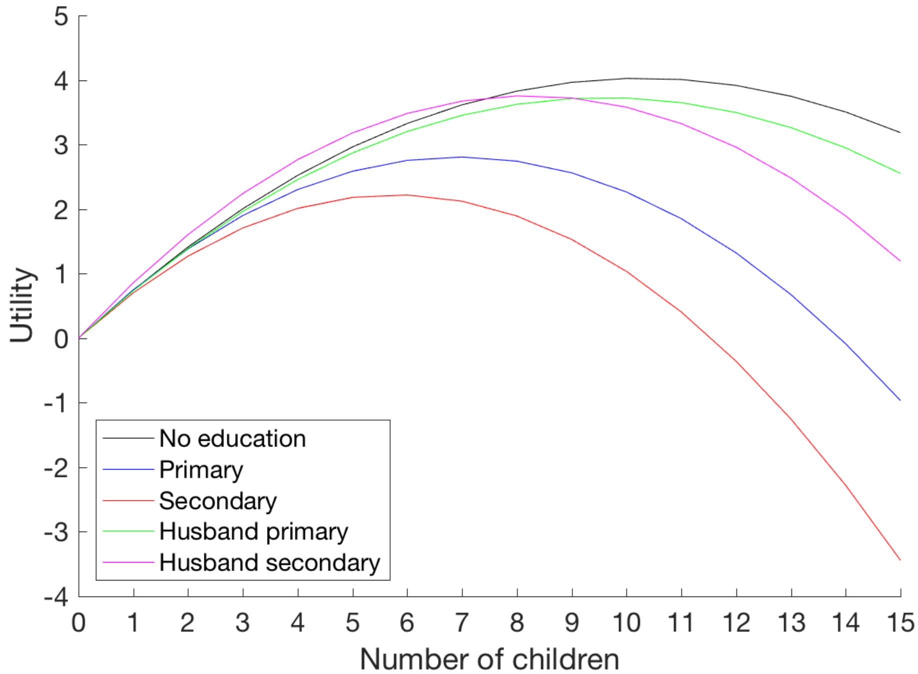


Table 7.1: Permanent Characteristics by Simulated Type

	Type 0	Type 1	Type 2
No education	44.8	38.8	42.3
Primary	36.8	42.3	35.7
Secondary	18.4	18.9	21.9
Husb. no education	50.2	48.4	45.7
Husb. primary	19.5	20.4	20.3
Husb. secondary	30.3	31.3	34.0
Poorest	39.3	40.4	34.0
Middle	36.4	35.1	32.8
Richest	24.3	24.5	33.2
Married before 18	26.9	28.0	25.5
Married between 18-23	55.5	53.7	48.7
Married after 23	17.5	18.3	25.8
Access	2.6	2.5	2.7
Sample percentage	20.9	6.6	72.6

All variables are expressed in percentage, except for Access.

Table 9.4 (appendix) provides the parameter estimates of the type equation, with type zero parameters normalized to zero. In addition, Table 7.1 shows the average characteristics of women by simulated type, where types are drawn 200 times for each woman. Type zero, one and two represent 20.9%, 6.6% and 72.6% of the sample respectively. Type zero and type one have similar permanent characteristics, except that type zero is more likely to have no education and type one is more likely to have primary education. Type two, which is unlikely to receive the intervention, tends to be more educated, have more educated husbands, be more wealthy, get married latter and have slightly better access to quality than the two other types.

Table 7.2 is derived by drawing types 200 times for each women. I then simulate choices, pregnancies and program exposure conditional on a woman's observed state variables at baseline, midterm and endline. I report the percentage of women that that make each choice and the percentage that become pregnant in the pooled sample, by type. I also provide the average level of exposure at midterm and endline by type.

Table 7.2: Choices, Pregnancies and Exposure by Simulated Type

	Type 0	Type 1	Type 2
No sex	11.9	15.5	14.9
Unprotected sex	58.5	61.0	54.5
Protected sex	29.5	23.5	30.6
Pregnant	19.0	15.9	16.9
Midterm exposure	1.3	2.8	-0.1
Endline exposure	1.5	3.1	0.2
Sample percentage	20.9	6.6	72.6

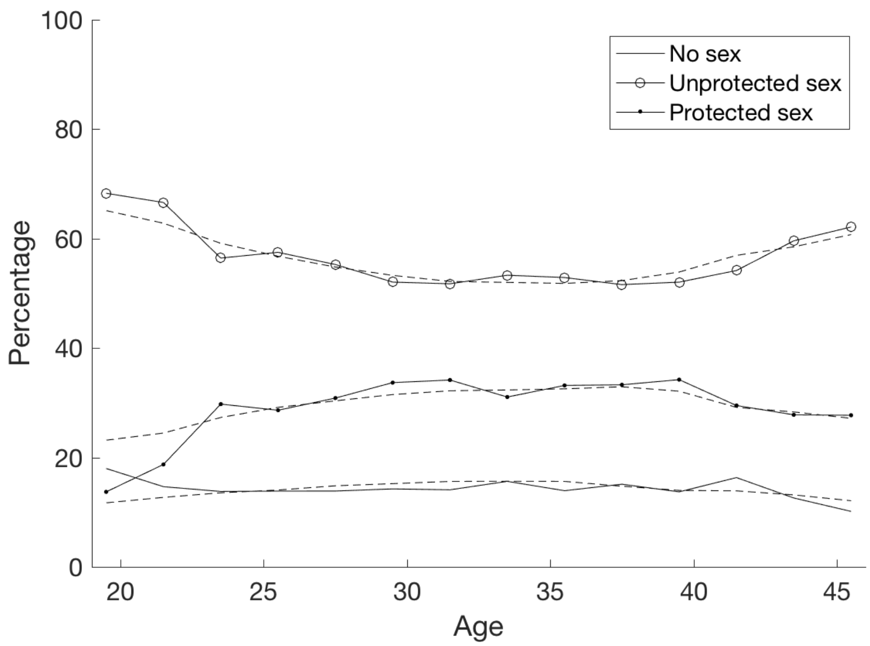
All variables are expressed in percentage, except for Midterm exposure and Endline exposure.

7.2. Model Fit

I assess the model fit by comparing the predictions of my model to the data. Baseline, midterm and endline observations are pooled, and model predictions are obtained by simulating choices 200 times for each woman, conditional on her observed state variables.

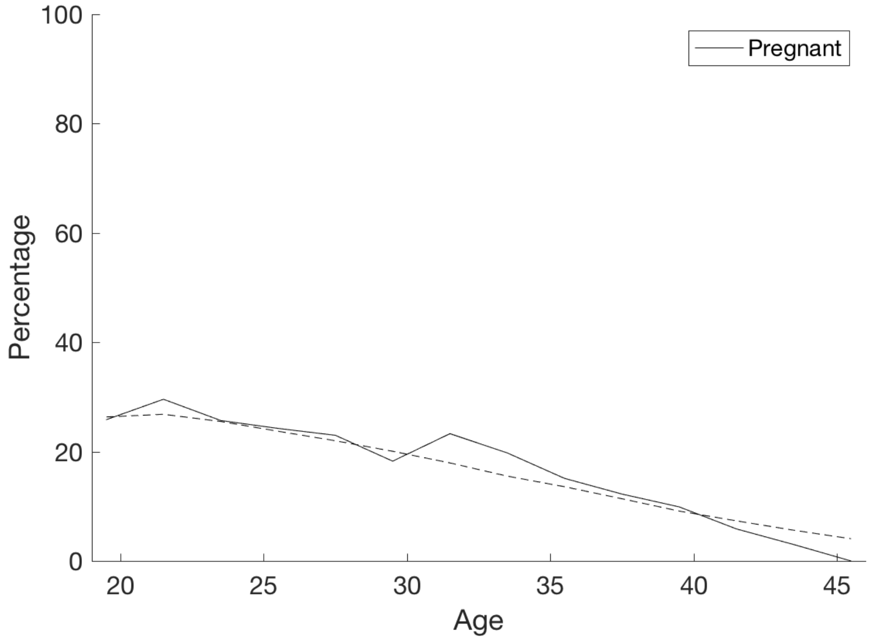
Figure 7.2 shows the percentage of women who choose to be abstinent, have protected sex or unprotected sex in the data (solid lines) and the simulated sample (dashed lines), averaged over two-year age bins.[3] The model fits the data well. Contraceptive use is low at younger ages and increases over the life cycle. This pattern is consistent with the parameter estimates, which imply that the cost of pregnancy increases with age and the marginal utility of children decreases with parity. On the other hand, the probability of pregnancy declines with age (figure 7.3), which explains the uptake of unprotected sex towards the end of the reproductive life cycle.

Figure 7.2: Choices



[3]The sample of married women under 19 is too small to be displayed by age in figure 7.2 and 7.3, but is included in the other model fit figures and tables.

Figure 7.3: Pregnancies at Baseline



The percentage of pregnant women decreases over the life cycle and is lower among those who use birth control (appendix figure 9.3). In addition, women are less likely to become pregnant if they gave birth recently. This can be seen in table 9.5 in the appendix for women under the age of 30.[4]

Table 7.3 shows that women with primary or secondary education are more likely to use contraceptives or be abstinent compared to women with no education. In addition, the model fits well the characteristics of the providers chosen by women (table 7.4) and the level of program exposure at midterm and endline (table 7.5). Finally, exposure is correlated with greater contraceptive use at midterm and endline (table 7.6).

[4]I focus on women under the age of 30 since older women are more likely to done bearing children.

Table 7.3: Choices by Education (%)

	Data	Model
No education		
Abstinence	13.3	13.4
Unprotected sex	61.2	60.4
Protected sex	25.5	26.2
Primary		
Abstinence	14.5	15.1
Unprotected sex	52.1	52.9
Protected sex	33.4	32.0
Secondary		
Abstinence	16.5	15.0
Unprotected sex	51.1	51.0
Protected sex	32.5	34.0

Table 7.4: Provider Choices (%)

	Data	Model
Chosen quality	0.691	0.680
Chosen distance	0.983	0.997
Chosen price	1.664	1.682

Table 7.5: Program Exposure

	Data	Model
Midterm exposure	0.48	0.41
Endline exposure	0.68	0.68

Table 7.6: Contraceptive Use by Exposure at Midterm and Endline (%)

	Data	Model
Not exposed ($\xi_t = 0$)	32.1	29.0
Exposed ($\xi_t > 0$)	43.2	43.9
All	36.2	34.6

SECTION 8
POLICY EXPERIMENTS

The estimated model allows me to simulate choices and pregnancies over the reproductive life of women, under different types of scenarios. I start by decomposing the increase in contraceptive use that occurred between 2011 and 2015 into three factors: women progressing through their life cycle (i.e. aging and having children), changes to the supply environment, and exposure to family planning programs. I use the sample of women who have both a baseline and an endline observation for this simulation exercise. The first line of table 8.1 shows the percentage of contraceptive users in the matched sample in 2011. Next, I simulate choices 200 times for each woman, conditional on her observed state variables in 2011. The model predicts that 25.21% of women use contraceptives at baseline. I then fix the supply and exposure variables to their baseline values and simulate choices and pregnancies from 2011 to 2015. In this simulation, the environment is kept constant and women are aging, which isolates the effect of the first factor. The next simulation is similar, except that I update all the provider variables to their endline values in 2013.[1] Exposure variables are kept to their baseline values (zero) in order to isolate the effect of the second factor. In the last simulation, I update both the provider and exposure variables in 2013.

Table 8.1: Effect Decomposition (%)

	Users
Baseline data	25.77
Baseline simulation	25.21
Fixed environment	25.54
Supply change	29.48
Supply change and exposure	35.56
Endline data	39.37

[1]The supply environment changes gradually between 2011 and 2015 in reality. I have limited provider data for the years between 2011 and 2015, so I update the provider variables halfway through this period, in 2013.

The model underestimates contraceptive use at endline (35.37% versus 39.37% in the matched sample). Nonetheless, the model suggests that 3.2% of the longitudinal increase in contraceptive use between 2011 and 2013 can be explained by aging, 38.1% by changes in the supply environment, and 58.7% by the ISSU awareness campaign.

In the next set of simulations, I evaluate the maximum impact of the most common family planning interventions: implementing an awareness campaign, reducing contraceptive prices, and increasing the quantity and quality of providers. I apply the endline environment (supply and exposure) to the baseline sample of women as a starting point to these simulations, in order to approximate as well as possible the current state of Dakar, Mbour and Kaolack.[2] I then simulate the choices and pregnancies of each woman 200 times, from her age in 2011 until the age of menopause (47). The initial state variables are taken from the baseline data and are updated in each period as pregnancies occur.

Table 8.2: Maximum Impact

	Current Users (%)	Completed Fertility
Reference	34.08	4.87
Price = 0	37.53	4.81
Quality = 1	37.97	4.80
Distance = 0	49.01	4.58
Exposure = 4	62.22	4.32

First, I keep the supply and exposure variables constant over time. Table 8.2 reports the predicted percentage of contraceptive users in the first period, as well as the average number of children per women at the end of this simulation. Next, I repeat this simulation under the following scenarios: contraceptives are free, all providers have the maximum level of quality (index equals one), there is no distance to travel to obtain contraceptives, and all women receive the four community programs. The goal is to evaluate the upper-bound, the maximum impact possible with each type of policy.

Table 8.2 indicates that offering contraceptives for free and increasing the quality index to the maximum for all providers would lead to a 10.1% and a 11.4% increase in contraceptive use, respectively. Note that contraceptives prices are already low at endline (4900 CFA on average for pills and injectables, see table 4.7).

[2] The baseline sample is representative of married women in 2011. Differences with a current cross-section of married women would be driven by long term demographic trends, such as younger cohorts getting married later or achieving more schooling.

The quality index is also high for many providers and equal to 0.701 on average at endline. Thus, the latter simulation should be interpreted as a 42.7% increase in the average quality of services.

The descriptive analysis in section 4.5 suggests that women are sensitive to travel costs, with the majority traveling by foot to their providers. In the extreme scenario where travel costs are entirely eliminated (for instance by delivering contraceptives through home visits), the percentage of contraceptive users increases by 43.8%. As a result, the average number of children per women would decline from 4.87 to 4.58. Exposing all women to the four community activities (the average exposure was 0.684 at endline) would have the greatest impact, increasing contraceptive use by 82.6% and reducing the average number of children per women to 4.32.

These simulations suggest that the price and quality of services are not the main factors that currently limit contraceptive use in urban Senegal. Travel costs, which include the time and monetary cost of traveling to a provider, and cultural barriers are greater obstacles. The latter includes personal or spousal opposition and misconceptions about side effects, which can be addressed through family planning programs.

I design, based on these findings, a set of polices that would be more realistic to implement (table 8.3). The simulation method and the reference are similar to the previous table. The first policy is to offer contraceptives for free in the public sector. The second is to ensure that all public health facilities have all five methods and the basic medical material in stock, that all their reproductive health staff has received an ISSU training, and that none impose restrictions based on age, parity or spousal consent.[3] The third simulation is to reduce the distance to each provider by 25%, which is equivalent to reducing the total cost of traveling by 25%. It could be achieved by expanding the public transportation system, which is currently limited in urban Senegal. The fourth policy is to expand the awareness campaign so that all women are exposed to at least two of the four community programs.

The last line in table 8.3 shows that combining all four policies would increase contraceptive use by 57.5% and reduce completed fertility from 4.87 to 4.49. Note that this represents the impact on all married women between the age of 15 and 47 in the year that the policies are implemented. The average life-cycle fertility does not decline much because the family size of older women is already determined. Table 9.6 shows that these policies would have a greater impact on younger women. For women under the age of 23,

[3]This policy would increase the endline quality index by 35.7% on average.

Table 8.3: Policy Recommendations

	Current Users (%)	Completed Fertility
Reference	34.08	4.87
Price = 0 in public sector	35.79	4.84
Improved quality in public sector	37.02	4.81
25% less travel cost	36.44	4.83
Exposure ≥ 2	45.61	4.66
All	53.67	4.49

combining all four policies would increase contraceptive use by 64.6% and reduce completed fertility from 5.12 to 4.38 children.[4]

[4]Women already have on average 1.0 children at the age of 23.

SECTION 9
CONCLUSION

In this paper, I evaluate the impact of several large-scale family planning interventions on the fertility decisions of married women in urban Senegal. Between 2011 and 2015, the Gates Foundation funded a broad range of interventions in order to increase the number of contraceptive users in Dakar, Mbour and Kaolack, three cities in Senegal. Supply-side interventions aimed at improving the quality of public providers by reducing contraceptive stockouts and offering additional training in family planning. Demand-side interventions employed radio programs, television programs, and community outreach to address the benefits of family planning, acceptance by religious leaders, and misconceptions about the harmfulness of contraceptives.

These interventions were not randomized, but they generated considerable variation in the supply and demand for contraceptives, which can be captured with a structural model. I specify a dynamic discrete choice model of fertility in which a married woman can decide, at each age, to be sexually active and whether or not to use birth control. If she opts for birth control, she selects a contraceptive provider based on price, quality and distance among all the providers that are located within a given distance of her dwelling place. The quality of a provider affects the satisfaction she derives from a visit and how effectively she uses her contraceptive method, and therefore the probability of pregnancy. In addition, a woman can be exposed to four community programs (home visits, community conversations, neighborhood groups and religious talks) that reduce her aversion towards contraceptives.

The model is estimated on a unique data set that includes all the contraceptive providers in Dakar, Mbour and Kaolack, linked to a longitudinal sample of married women in each city. The estimated model is then used to carry out several policy experiments. I start by decomposing into three different factors the increase in contraceptive use that occurred between baseline (2011) and endline (2015) in the longitudinal sample. During this four year period; (1) women progressed along their life cycle, aging and having children; (2) the supply environment changed, with an overall increase in provider quality, a decline in contraceptive prices, and an increase in the number of providers; (3) the demand-side interventions were implemented.

Results shows that contraceptive use increased from 25.8% in 2011 to 39.4% in 2015, and that 3.2% of this increase can be explained by aging, 38.1% by changes in the supply environment, and 58.7% by the awareness campaign.

In the second set of simulations, I compare the impact of different policies on contraceptive use and fertility after 2015. I find that further price reductions and quality improvements would minimally increase the percentage of contraceptive users. On the other hand, reducing travel costs and cultural barriers could have a substantial impact on contraceptive use. There remain widespread misconceptions about the harmfulness of contraceptives in urban Senegal, which can be addressed by expanding the awareness campaign that was implemented between 2011 and 2015 in Dakar, Mbour and Kaolack.

APPENDIX

Figure 9.1: Senegal Population (in Millions)

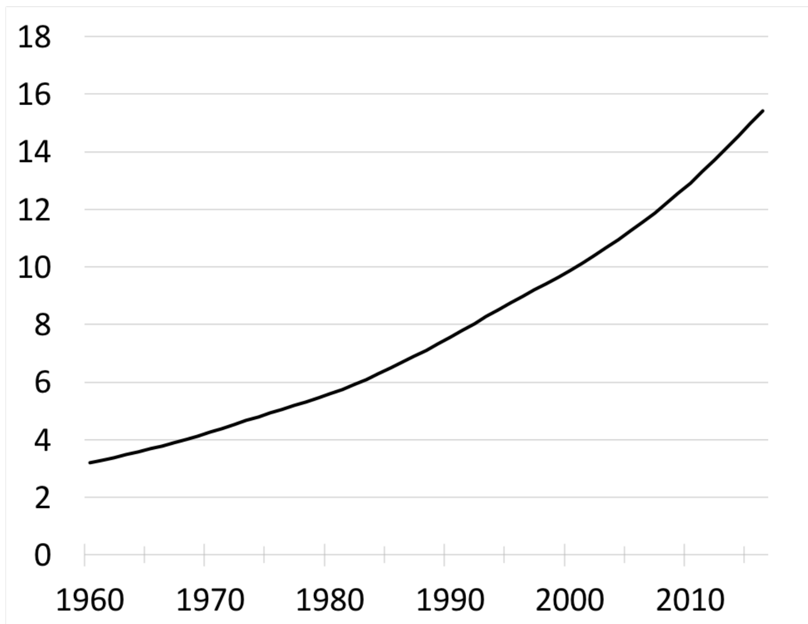


Figure 9.2: Distribution of Prices

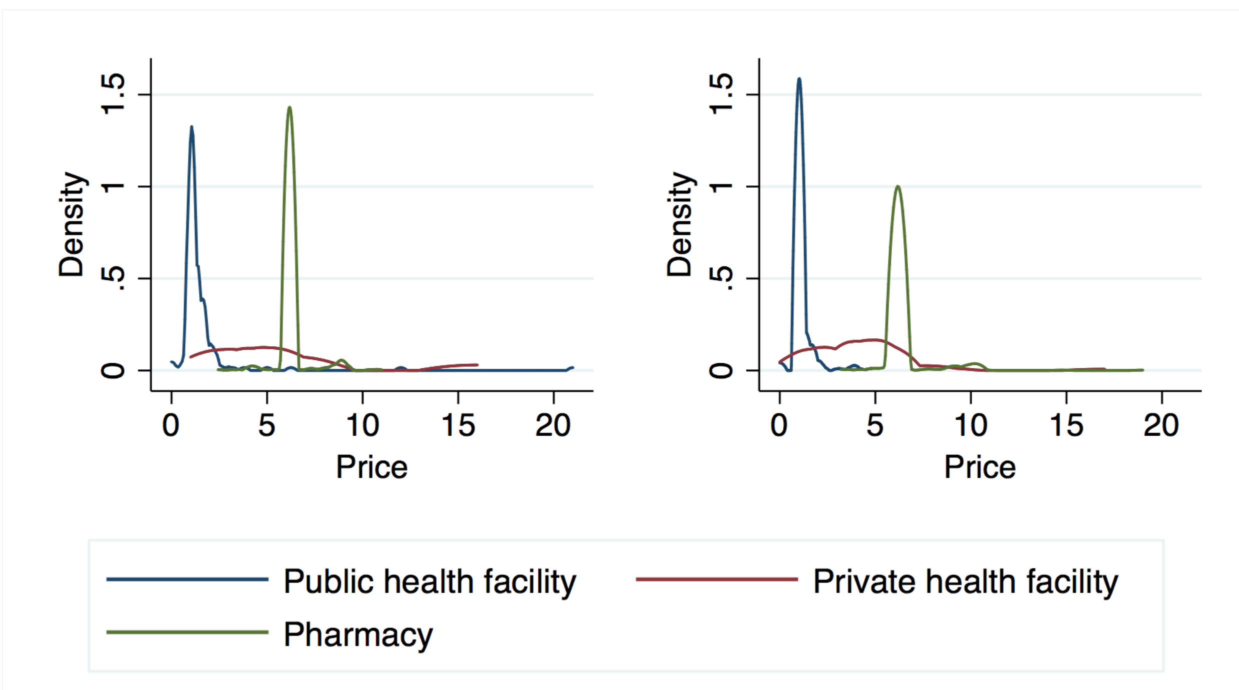


Table 9.1: Utility Function Estimates

Parameter	Variable	Estimates	SE
α_1	s_t	1.845	0.217
α_2	b_t	-1.356	0.212
$\alpha_{3,1}$	$b_t \times I(\mu = 1)$	-0.478	0.131
$\alpha_{3,2}$	$b_t \times I(\mu = 2)$	-0.150	0.091
α_4	$b_t \times h_{ft}$	-0.258	0.064
α_5	$b_t \times h_{ft} \times q_{ft}$	0.738	0.103
α_6	$b_t \times d_{ft}$	-0.443	0.053
$\alpha_{7,1}$	$b_t \times d_{ft} \times I(\omega = 1)$	0.049	0.015
$\alpha_{7,2}$	$b_t \times d_{ft} \times I(\omega = 2)$	0.084	0.018
α_8	$b_t \times p_{ft}$	-0.109	0.016
$\alpha_{9,1}$	$b_t \times p_{ft} \times I(\omega = 1)$	0.028	0.009
$\alpha_{9,2}$	$b_t \times p_{ft} \times I(\omega = 2)$	0.058	0.011
α_{10}	$b_t \times \xi_t$	0.373	0.046
α_{11}	n_t	0.739	5.974
$\alpha_{12,1}$	$n_t \times I(\mu = 1)$	0.044	0.137
$\alpha_{12,2}$	$n_t \times I(\mu = 2)$	-0.195	0.068
$\alpha_{13,1}$	$n_t \times I(e = 1)$	0.026	0.056
$\alpha_{13,2}$	$n_t \times I(e = 2)$	-0.013	0.067
$\alpha_{14,1}$	$n_t \times I(e^h = 1)$	-0.006	0.061
$\alpha_{14,2}$	$n_t \times I(e^h = 2)$	0.132	0.058
α_{15}	n_t^2	-0.014	0.008
$\alpha_{16,1}$	$n_t^2 \times I(\mu = 1)$	-0.024	0.016
$\alpha_{16,2}$	$n_t^2 \times I(\mu = 2)$	0.006	0.008
$\alpha_{17,1}$	$n_t^2 \times I(e = 1)$	-0.020	0.007
$\alpha_{17,2}$	$n_t^2 \times I(e = 2)$	-0.029	0.009
$\alpha_{18,1}$	$n_t^2 \times I(e^h = 1)$	-0.002	0.007
$\alpha_{18,2}$	$n_t^2 \times I(e^h = 2)$	-0.018	0.007
α_{19}	φ_t	-0.619	54.98
α_{20}	$\varphi_t \times t$	-0.138	0.059
α_{21}	$\varphi_t \times \varphi_{t-1}$	-2.489	0.778
α_{22}	$\varphi_t \times (1 - \varphi_{t-1}) \times \varphi_{t-2}$	-0.948	0.184
δ	Discount factor	0.9 (fixed)	
ρ	Nest coefficient	0.252	0.031
σ	Standard deviation	0.426	0.006

Table 9.2: Exposure Equation Estimates

Parameter	Variable	Estimates	SE
β_0	Constant	1.210	0.044
$\beta_{1,1}$	$I(\mu = 1)$	1.564	0.023
$\beta_{1,2}$	$I(\mu = 2)$	-1.334	0.014
β_2	$I(y = 2015)$	0.282	0.026
$\beta_{3,1}$	$I(e = 1)$	0.003	0.019
$\beta_{3,2}$	$I(e = 2)$	-0.018	0.024
$\beta_{4,1}$	$I(\omega = 1)$	-0.021	0.020
$\beta_{4,2}$	$I(\omega = 2)$	-0.037	0.022
β_5	t	0.002	0.001

Table 9.3: Pregnancy Equation Estimates

Parameter	Variable	Estimates	SE
γ_0	Constant	-2.216	0.749
$\gamma_{1,1}$	$I(\mu = 1)$	-0.287	0.191
$\gamma_{1,2}$	$I(\mu = 2)$	-0.042	0.102
γ_2	t	0.196	0.051
γ_3	t^2	-0.005	0.001
γ_4	φ_{t-1}	-1.162	0.104
γ_5	b_t	-2.319	0.120

Table 9.4: Type Equation Estimates

		Type 1		Type 2	
Parameter	Variable	Estimates	SE	Estimates	SE
τ_0	Constant	-1.110	0.223	1.033	0.134
$\tau_{1,1}$	$I(e=1)$	0.306	0.175	-0.064	0.109
$\tau_{1,2}$	$I(e=2)$	0.222	0.228	0.002	0.143
$\tau_{2,1}$	$I(e^h=1)$	0.047	0.201	0.083	0.121
$\tau_{2,2}$	$I(e^h=2)$	0.003	0.188	0.060	0.114
$\tau_{3,1}$	$I(\omega=1)$	-0.105	0.178	-0.003	0.112
$\tau_{3,2}$	$I(\omega=2)$	-0.062	0.206	0.379	0.127
$\tau_{4,1}$	$I(a_1=1)$	-0.111	0.183	-0.120	0.110
$\tau_{4,2}$	$I(a_2=1)$	-0.046	0.239	0.333	0.140
τ_5	ξ	-0.038	0.055	0.031	0.028

Figure 9.3: Pregnancies at Baseline by Method

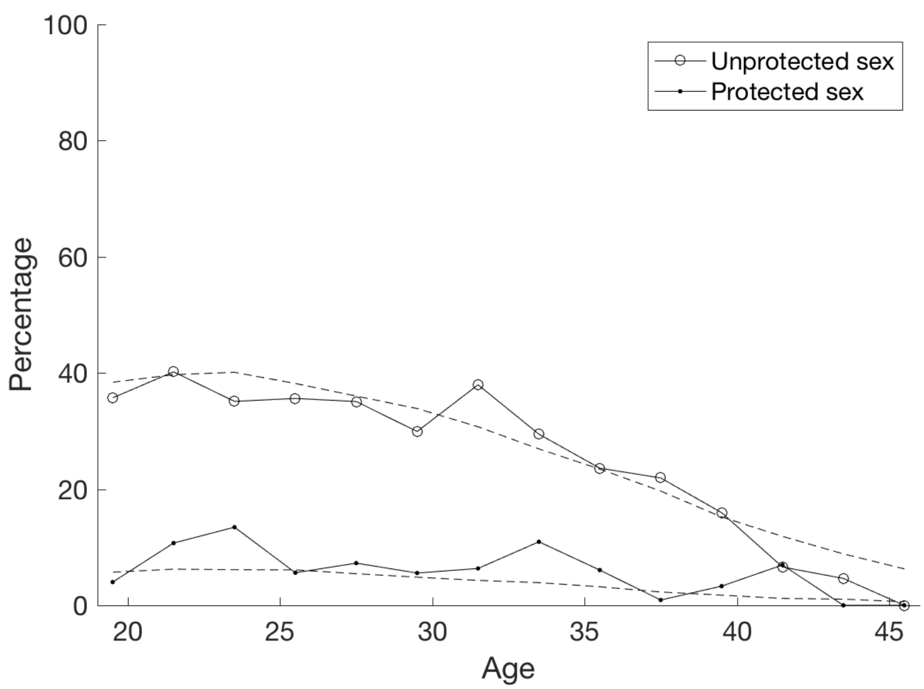


Table 9.5: Percentage of Women Under Age 30 Who Are Pregnant by Time Since Last Pregnancy

	Data	Model
Last pregnancy:		
One year ago	11.6	11.9
Two years ago	25.1	26.1
Over two years/never pregnant	33.1	30.3

Table 9.6: Maximum Impact (Women Under Age 23)

	Current Users (%)	Completed Fertility
Reference	28.45	5.12
Price = 0	31.67	5.00
Quality = 1	31.84	4.98
Distance = 0	42.26	4.56
Exposure = 4	55.01	4.04

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