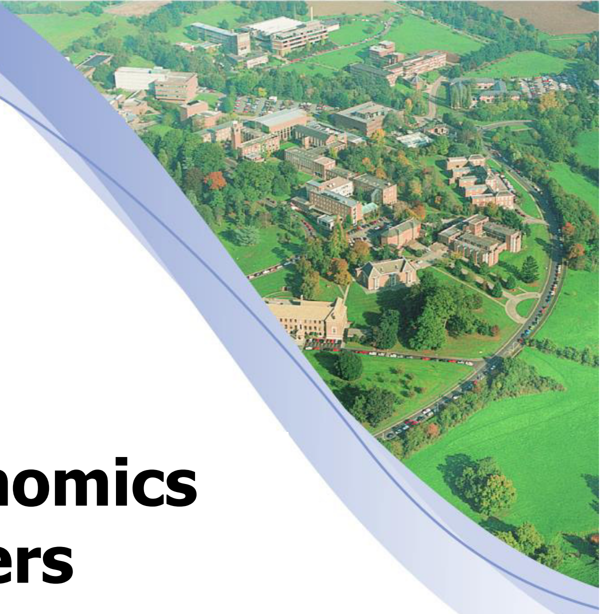

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Shared Decision-Making: Can Improved Counseling Increase Willingness to Pay for Modern Contraceptives?

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Shared Decision-Making: Can Improved Counseling Increase Willingness to Pay for Modern Contraceptives?

Susan Athey Katy Bergstrom Vitor Hadad Julian C. Jamison

Berk Özler Luca Parisotto Julius Dohbit Sama*

September 16, 2021

Abstract

Long-acting reversible contraceptives are highly effective in preventing unintended pregnancies, but take-up remains low. This paper analyzes a randomized controlled trial of interventions addressing two barriers to long-acting reversible contraceptive adoption, credit, and informational constraints. The study offered discounts to the clients of a women's hospital in Yaoundé, Cameroon, and cross-randomized a counseling strategy that encourages shared decision-making using a tablet-based app that ranks modern methods. Discounts increased uptake by 50 percent%, with larger effects for adolescents. Shared decision-making tripled the share of clients adopting a long-acting reversible contraceptive at full price, from 11% to 35 percent%, and discounts had no incremental impact in this group.

JEL Codes: I15; J13; C13; C14

Keywords: Family Planning; Fertility; Long-Acting Reversible Contraceptives; Heterogenous Treatment Effects;

*Athey: athey@susanathey.com, Stanford University. Bergstrom, kbergstrom@worldbank.org, The World Bank. Hadad, vitorh@stanford.edu, Stanford University. Jamison, J.Jamison@exeter.ac.uk, University of Exeter. Özler (corresponding author): bozler@worldbank.org, The World Bank. Parisotto: lparisotto@worldbank.org, The World Bank. Sama, dohbit@yahoo.com, Hôpital Gynéco-Obstétrique et Pédiatrique de Yaoundé (HGOPY), Université de Yaoundé I. The study team is grateful to the administration of HGOPY, which is the site for this experiment. In particular, we thank Ewolo Esther, the team of nurse counselors at HGOPY, led by Hildegarde Ebenye, Juliette Kegne, Denise Noupele, who are too numerous to list here. We are also grateful to Prof. Mbu Robinson Enow, Prof. Fru Buzshi Angwafo III, Prof. Pascal Foumane, Dr. Emma Woks, and Mr. Julien Ondoua, all at HGOPY, for their support in facilitating this study. The tablet-based job support tool (the *app*) used by nurse counselors was developed in collaboration with the Cameroon Ministry of Health's Department of Family Health (Direction de la Santé Familiale, MinSanté): special thanks go to Prof. Mbu Robinson Enow and Dr. Jeanette Afounde for their support. Drs. Anne E. Burke (Johns Hopkins University) and Maria Steenland (Brown University) provided valuable comments throughout the development of the *app* and Dr. Burke kindly tested early versions. Jake Robyn and Jean Claude Taptue Fotso from the World Bank were instrumental in providing initial support for this study, and Yohana Dukhan provides continued support. We thank HEREG and Dr. Njoumemi Zakariaou for assisting with project management and data collection. We are grateful for comments we received from seminar participants at UCLA, ASSA, The World Bank, FHI360 and CEGA. Funding from the World Bank's Strategic Impact Evaluation Fund, Knowledge for Change Program, Global Financing Facility, and Research Support Budget is gratefully acknowledged. The study is registered at the AEA RCT registry (AEARCTR-0003514) and clinicaltrials.gov (NCT03733678).

1 Introduction

Globally, the maternal mortality ratio (MMR) remains high at 211 maternal deaths per 100,000 live births in 2019, despite significant reductions since 2000 (WHO, 2019). In sub-Saharan Africa the MMR is 534, implying that one in 38 women aged 15 will eventually die from a maternal cause. As many of the causes are preventable or treatable, substantial reductions in MMR can be achieved on the intensive margin – by expanding coverage and improving the quality of routine reproductive health care for pregnant women (Kassebaum et al., 2016).

However, there is also ample room for improvement on the extensive margin: nearly half of all pregnancies worldwide are considered unwanted or mistimed (Sully et al., 2020). In Cameroon, the setting for our experiment, the share of such births is twice as high among adolescents as adults (DHS, 2018), and the risk of complications in pregnancy and childbirth is also higher (WHO, 2019). Therefore, increasing access to contraception, especially among adolescents, can contribute to large reductions in MMR. Delayed fertility is associated with improved maternal and child health outcomes (see Baird et al. 2011, and citations within), while unintended pregnancies are strongly predictive of short inter-pregnancy intervals, which are in turn positively associated with babies being born prematurely, at low birth weight, or small for their gestational age (DeFranco et al., 2015; Frost et al., 2014). Lower fertility rates may also contribute to economic growth through increased female labor supply (Bloom et al., 2009, 2020).

Modern contraceptive technology is highly effective in preventing unintended pregnancies. However, adoption in many low- and middle-income countries (LMIC) remains low: among women in LMICs who report wanting to avoid a pregnancy, about a quarter of women and half of adolescent females also report not using a contraceptive method (see Sully et al. 2020). Our formative qualitative work in Cameroon shows that there are a multitude of demand-side factors impeding adoption: concerns over side effects, misconceptions about methods, financial cost, concerns over discretion, and opposition from parents, spouses, or partners. These barriers are further exacerbated by supply-side problems, such as stock-outs of contraceptives, lack of trained health providers, and provider bias against recommending certain contraceptive methods to adolescents and women without children.

We conducted a randomized experiment to tackle two of these barriers: cost and uncertainty about returns from adopting contraceptives. The experiment was conducted at a women and children's hospital in Yaoundé, Cameroon, and it constituted the pilot phase for an adaptive experiment that was being planned at the hospital. We developed a tablet-based *app*, which assists healthcare providers conducting family planning (FP) counseling sessions. During a structured discussion, the *app* records the clients' fertility plans, needs, and preferences regarding contraceptive methods. The main innovation that the *app* brings to FP counseling is an internal algorithm to rank methods according to their suitability for the client's context. In the *shared decision-making* treatment (SDM), the *app* reveals the most suitable method and the provider suggests to the client that they discuss this method first. This contrasts with the *individual decision-making* treatment (IDM), in which the provider asks the client to decide which method they'd like to discuss first, choosing from the full, unranked set of modern contraceptives. SDM is thus aimed at providing the clients with better information tailored to their individual needs, while IDM is meant to resemble the *status quo* in contraceptive counseling. We also cross-randomized a *discount* treatment, in which the *app* revealed randomly-assigned discounts for modern contraceptive methods. The *discount* treatment relaxes the credit constraints that prevent clients from adopting LARCs due to their high upfront costs.[1]

The tablet-based *app* collects detailed information on client characteristics and choices. We are interested in whether the client adopted (i) a LARC (the IUD or the implant), (ii) a short-acting method, or SARC (the injectable or the pill), or (iii) no modern contraceptive method. We find that discounts for LARCs had a large effect on their adoption: while 32% of all eligible clients adopted a LARC at full price (CFA 4,000 or approximately USD 7.25), this share increased to 45% at mid prices (USD 1.8 or 3.6), and 48% at low prices (free or USD 0.25). Adolescents were particularly price-sensitive: take-up increased from 12% at full price to 42% at mid and 55% at low prices. The increase in LARC adoption is accompanied by a similar reduction in the share of clients adopting no modern method, rather than a shift from SARCs.

SDM was also effective in increasing LARC uptake, with this effect significantly interacting with the *discount* treatment. Under IDM, only 11.4% of the clients adopted a LARC at full price. This share more than tripled to 35.3% under SDM. SDM may have also made clients less price-sensitive: discounts, on average, increased LARC uptake by 17 percentage points (pp) under IDM but the point estimate is close to zero under SDM (although the difference between the two effects is only statistically significant at the 10% level). We present a model of individual utility maximization, where clients care about the price and the perceived returns from adopting a LARC, that is consistent with this finding (Appendix C). The results indicate that a simple behavioral nudge during counseling can increase the willingness-to-pay for LARCs to a level sufficiently high so as to make discounts ineffective in further increasing adoption.[2]

Our paper is related to the literature on the effect of providing vouchers and other price changes on contraceptive use (McKelvey et al., 2012). Prior research has shown that providing vouchers that fully or partially subsidize FP services increase the use of modern contraceptives among women (Ashraf et al., 2014; Bellows et al., 2016; Anukriti et al., 2021). Shah et al. 2021 finds that free provision of modern contraceptives to adolescent females at girls' clubs in Tanzania did not lead to increased take-up. Ashraf et al. (2014) find that provision of vouchers to married women in the presence of husbands reduces their redemption compared to them being offered when they are alone in the setting of a large clinic in Lusaka. Recent quasi-experimental studies also indicate that women, unmarried young women in particular, may be responsive to contraceptive prices (Rau et al., 2017), with adolescents in the U.S. selecting LARCs and continuing to use them long-term (Mestad et al., 2011) and programs encouraging clinics to stock and provide free LARCs to low-income women causing decreases in teen birth rates (Lindo and Packham, 2017).

Our paper contributes to this literature by demonstrating that offering FP counseling and discounts to female clients at healthcare facilities can achieve large reductions in the number of women not using a modern method but wanting to delay pregnancy. While we find that discounts are effective

[1] The high upfront costs of LARCs, along with high cost of removals, contrast with the per-month cost of protection from unintended pregnancies. The IUD can be used for up to 10 years while the implant lasts three-to-five years. In contrast, the injectable (Depo-Provera) provides protection for only three months, while the pill needs to be taken everyday.

[2] In principle, there could be negative consequences of the counseling intervention for women's autonomy and decision-making. Using follow-up surveys with a latter cohort of clients in the adaptive experiment, We found no differences between the two counseling arms in terms of client satisfaction or their willingness to return to the hospital for FP services in the future (see Section 4.2).

among women specifically seeking FP services, they are even more effective among clients who were seeking other services and were simply offered FP counseling before they left the hospital. Consistent with the literature, we find that such patients and adolescent females are particularly price-sensitive when it comes to adopting modern contraceptives.

Our study is also related to a growing literature in the U.S. on counseling interventions – such as peer counseling, a *waiting room app* for contraceptive counseling, and motivational interviewing techniques allowing the client to articulate goals and discuss plans – that showed promise in leading to higher levels of knowledge of contraceptive effectiveness, increased interest in adopting the implant, and higher rates of LARC uptake (Gilliam et al., 2014; Church et al., 2017; Wilson et al., 2014). It is also related to the literature in economics on providing sexual and reproductive health information to adolescents, young women, and to their spouses/partners (Dupas, 2011; Dupas et al., 2018; Duflo et al., 2015; Ashraf et al., 2020).

We contribute to this literature by testing a counseling approach (SDM) that allows for shared decision-making and comparing it to a counseling approach that mimics the status quo informed choice model IDM), in which individuals are given extensive information to make their own independent choices (Holt et al., 2017). We show that SDM substantially increases clients' willingness to pay for LARCs without reducing their level of satisfaction. If an individual is risk averse and adopting a LARC is perceived to be riskier, reducing uncertainty by suggesting that a LARC may be the most suitable method for the client might encourage its adoption (Cortés et al., 2021). In this sense, our paper is also related to a literature in behavioral science as applied to decision-making in health, in particular the key role of defaults and choice architecture (Johnson et al. 2005, among others). There is a general sense that agency (being involved in decisions, rather than being told what to do) is especially important for compliance in medical contexts (Donovan, 1995) – beyond the simple fact that it is also likely to produce better decisions in the first place – in the sense of matching personal preferences.

2 Experiment design

2.1 Setting and target population

The study was conducted at the Hôpital Gynéco-Obstétrique et Pédiatrique de Yaoundé (HGOPY), a women's hospital in the capital of Cameroon. In preparation for an adaptive experiment aiming to reduce unintended pregnancies among its clients, the study team organized a pilot in December, 2019. This phase served to introduce the *app* to nurse counselors; provide FP training to nurses in other units, such as maternity and gynecology; iron out the study protocols; and, perhaps most importantly, get all trained nurses to become comfortable with providing FP counseling under either approach – IDM and SDM – using the *app*. Despite the declaration of the global pandemic by the WHO in March, 2020, which reduced the number of clients presenting at HGOPY, these goals were successfully achieved by June 9, 2020. However, partly due to the disruptions caused by the pandemic, the study team was not ready to launch the adaptive experiment at that time. Instead, the team decided to run a static experiment with fixed and equal probabilities of assignment to each of the two interventions that were cross-randomized: *discounts* and *counseling*, which are discussed in detail later in this section. This experiment ran for nine months until the launch of the adaptive experiment on March 9, 2021 and provides the basis for this study.

Women aged 15-49 who received FP counseling at HGOPY by a trained provider using the *app* during the pilot were included in the study. Exceptions were clients who: (i) wanted to become pregnant within the next 12 months, (ii) were pregnant at the time of their consultation and had not yet come back to give birth at HGOPY by the end of the pilot, and (iii) completed their consultation without being exposed to either intervention.[3] During the study period, 1,008 clients were counseled at HGOPY, 784 of whom were eligible. 57% of eligible clients presented at the FP unit – either seeking to simply receive information; adopt a new method; switch to another method; or renew, manage the side effects of, or discontinue their current method. The remaining clients mainly presented at the maternity and gynecology wards: some had just given birth; some were pregnant and receiving ante-natal services; some might have returned to the hospital postpartum for a check-up or for their infants to receive vaccinations; yet others might have presented with a gynecological problem. Table A1 shows the characteristics of the study sample. The average client is 29 years old and 10% of the sample is under the age of 20. The sample is more or less equally divided between women who are single, cohabiting with a partner, and married. Approximately a quarter of them are students. The average number of children is 2.75 and 25% of clients report wanting no more children. Few clients were using any modern contraceptives at the time of their counseling session.

2.2 Interventions

The interventions are centered around the use of a newly developed tablet-based *app* (see Appendix E for a detailed description of the *app* and its main features). For the purposes of our study, the app serves as both the platform through which the counseling approach and prices of contraceptive methods can be randomly assigned to each client and the data collection tool to assess the impacts of these interventions.

2.2.1 Discounts for modern contraceptive methods

Eligible clients who received a FP consultation by a trained provider using the *app* were offered randomly varying discounts for modern contraceptives.[4]). The four modern contraceptive methods available at the hospital were grouped into two categories: LARCs (i.e., the copper IUD and the implant) or SARCs (i.e., the pill and the injectable). LARCs were offered at five different price levels with equal probability, which we collapse into three bins for statistical power: High (CFA

[3] We could not yet observe the outcome (contraceptive uptake) for clients in the second category. Clients in the third group include, for example, women who wanted to address the side-effects of their current method: such clients would be consulted with the *app*, but if they chose to continue using their method and did not need to renew it, they would not be exposed to any of the interventions.

[4] The typical use effectiveness of modern methods vary widely: while 0.05% of women using the implant experienced an unintended pregnancy within the first year of use, the same figures were 0.8% for the copper IUD, 6% for the injectable (Depo-Provera), 9% for the pill, and 18% for the male condom. The lactational amenorrhea method (LAM), when used correctly, is as effective as a short-acting method for up to six months after giving birth (see: Trussell and Guthrie 2011, Table 3.2.

4,000), Mid (CFA 2,000 or 1,000), and Low (CFA 150 or Free). SARC prices were cross-randomized at two price levels with equal probability: Full price (CFA 1,250 for the injectable and 1,500 for the pill) or for free.[5] Both short-acting methods need to be renewed every three months and the clients can do so at the same price offered at the initial consultation, which is valid for a period of one year, representing three renewals.

Two details about implementation matter. First, the prices for all modern methods were revealed at once and *after* the client had chosen a method they wanted to adopt, unless they inquired about prices earlier on in the counseling session.[6] This decision was made after careful deliberation with the healthcare providers at the hospital and based on established best-practices and ethical norms.[7] Second, the reader might worry about the clients (alone or in collaboration with the providers) trying to 'game' the system to receive higher discounts - for example, by asking the counselor to start a new *app* session or by returning later. Carefully developed study protocols for return clients, monitoring the data from the tablets (including meta- and para-data), and monthly audits of HGOPY's own administrative data allows us to rule out the possibility of clients redrawing a new set of prices.

2.2.2 Counseling approach

The structure of the counseling session guided by the *app* is not fundamentally different than the accepted best practices used around the world. The main innovation that it brings to FP counseling is a small but important paradigm shift with respect to shared decision-making: the app uses an algorithm to internally rank methods from most to least suitable for the client's preferences. In the established, or *status quo*, approach to counseling, the client is given information about all contraceptive methods and asked to choose the method she would like to discuss. The counselor is expected to provide no guidance or advice during this *individual decision-making* process. In contrast, in our alternative approach, the *app* encourages *shared decision-making* by revealing the most suitable method for the client according to the *app*'s internal algorithm. In order to test the effectiveness of this approach against the status quo, clients were randomly assigned to one of two interventions – each mimicking one approach:[8]

1. **Individual Decision-Making (IDM):** The tablet displays all available modern contraceptive methods that have not been ruled out by the client or contraindicated due to medical eligibility. The provider gives basic information on each available method (in order of the methods displayed on the tablet screen, which is randomized) covering its use, duration, and typical use effectiveness. These quick descriptions are designed to take 1-2 minutes for each method, or 5-6 minutes overall. The counselor then asks the client which method she would like to discuss, and provides detailed information with the help of the relevant cue card (see

[5]Due to low take-up of SARCs among the study population and the lack of impact of offering discounts for SARCs, the study team discontinued the cross-randomization of SARC prices on January 20, 2021. This implies that SARCs were offered at full price to everyone for approximately the last two months of the pilot study period.

[6]Only 4% of clients asked to see the random discounts before choosing a method.

[7]The clients were free to choose a different method, or no method at all, once the discounts were revealed.

[8]This randomization occurs towards the end of the consultation when the clients are ready to choose a method, after the discussion necessary for the client to make an informed choice but before the random discounts are revealed.

Appendix section E.4 for an example of a cue card). The client can then either choose this method or discuss another method (of her choice from the same unranked list). This process is repeated until a decision is made.

2. **Shared Decision-Making (SDM):** The tablet *only* displays the most suitable method for the client according to the ranking algorithm of the *app*. The provider tells the client that "...while there are a number of suitable methods for her, based on their discussion, the displayed method is most suitable for her needs," and asks her if she would like to discuss this method first. If the client answers 'no,' then the next highest ranked recommendation is displayed, and the process is repeated until the client decides to discuss the recommended method (or decline all of them). When the client answers 'yes,' the provider uses the appropriate cue card to describe the method in detail. The client can then decide whether to adopt this method or discuss the next method recommended by the *app*. Again, this process is repeated until a decision is made.

Our experiment aims to isolate the effect of telling the client that the *app* recommends one method as being most suitable for her needs, rather than simply asking her to decide which method she would like to discuss from a list of unranked options.[9]

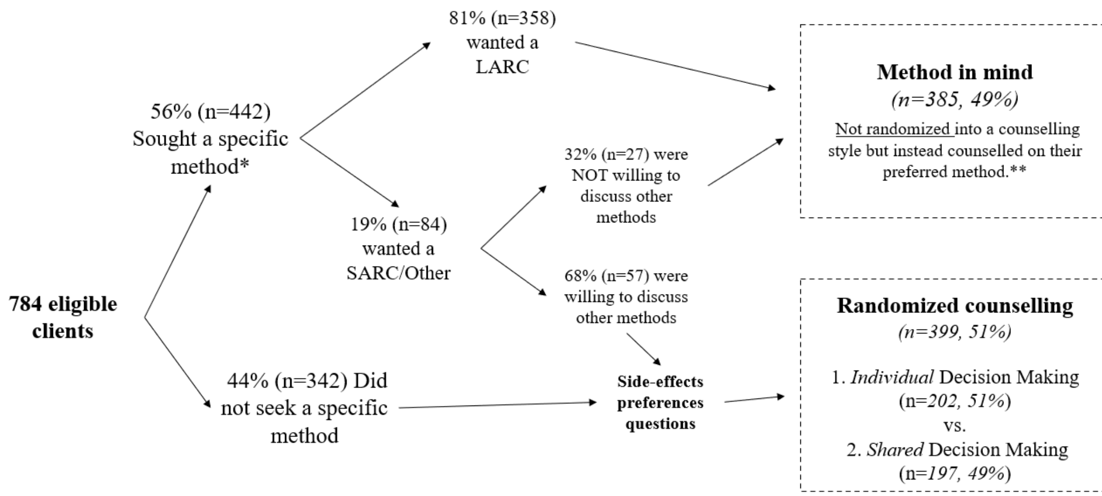
2.3 Experimental design

All eligible clients were randomly assigned to a set of contraceptive prices.[10] However, not everyone was assigned to a counseling condition: slightly over half of the eligible clients visited the hospital seeking a specific method, which they either wanted to adopt or renew.[11] The pilot phase of our study clearly revealed that such clients do not want, or need, to sit through a time-consuming session where all methods are described to them in detail. Figure 1 shows a simplified flowchart of the paths taken by first-time clients through the app.

[9]In the behavioral science literature, it is sometimes claimed that *joint* evaluation of options (*IDM* in our case) encourages more reasoned decision-making than does *separate* evaluation (*SDM* here), and hence superior outcomes, in part because it focuses attention on relevant dimensions rather than irrelevant biases such as, e.g., gender (Bohnet et al., 2016). In our setting, however, the ranking is specifically tailored to the client's preferences and, therefore *SDM* is designed to try to overcome biases directly. If anything, given that many clients walked away having adopted no modern method (as we will see in Section 4.2), the study team was more concerned about choice overload under *IDM*.

[10]Contraceptive prices and the counseling style are fixed for each client for one year per the random allocation at their initial visit, meaning that return clients face the same set of prices if they want to adopt a new method or switch their current one. They are also counseled using the same style – should there be a need for another session. Removals of LARCs are free for all study participants.

[11]We tried to make sure that these clients were expressing a strong intention to adopt a specific method: the question in the *app* reads "is there a specific method that you absolutely want to adopt?"



Notes: * Or wanted to renew their current method without discussing other methods (approximately 10% of this group of clients).
** In rare cases where a client's preferred method is contra-indicated they were counselled on the next most suitable method according to a default ranking.

Figure 1: FP counseling flowchart.

For clients seeking to adopt a specific method, the *app* follows a slightly different protocol - depending on whether that method is a LARC or not. Clients who want to adopt or renew a LARC are directed to the method choice section after a quick check on their medical history and a brief refresher on their desired method: approximately 80% of clients seeking to adopt a specific method fall into this category. In contrast, for the remaining 20% who want to adopt or renew a SARC (or other methods with lower typical use effectiveness), the *app* prompts the provider to inquire whether the client would be willing to discuss other methods that are more effective in preventing pregnancies and might be more suitable for her. 68% of such clients were willing to consider other methods and were thus eligible to be randomly assigned to a counseling intervention, while the remaining clients were directed to the method choice section to adopt or renew their preferred (non-LARC) method. This resulted in roughly half of the clients being randomly assigned to a counseling intervention, while the other half were counseled on their preferred method. We refer to the latter group as having a *method in mind*, or *MiM* for short.

3 Data and outcomes

3.1 Data

The *app* collects a rich set of client characteristics, including demographics, weight and blood pressure, as well as relevant medical and birth history. It also records the client's fertility preferences, prior experience with contraception, whether and why they seek to adopt a specific method, their preferences regarding side effects and, most importantly, which method - if any - they adopted at the end of the consultation. For each method discussed during the counseling session and not chosen by the client, the *app* records the reason why she did not want to adopt it. The result is a rich database containing adoption decisions, along with relevant client characteristics and preferences.[12]

3.2 Outcomes

The primary outcomes considered in this study are the shares of clients who adopted (i) a LARC, (ii) a SARC, or (iii) neither. We denote the last group as having *adopted no modern method* although it includes clients who adopted LAM, condoms, or other traditional methods. We mainly focus our attention on the adoption of LARCs due to low demand for SARCs among our study population (Table A4 provides a detailed breakdown of the method mix). The primary outcomes are constructed using data collected on the tablets, which are cross-checked with hospital administrative records that are further verified by a third-party independent auditor. A non-negligible number of clients do not adopt a method during their initial visit but return to HGOPY to adopt a method later – e.g., after taking some time to think about their decision; having discussed it with their partners, spouses, or parents; needing to collect the money necessary to adopt the method; etc. For these clients, the data across consultations are linked so that the most up to date outcome is considered.[13] Similarly, some clients may return to the hospital to switch or discontinue their adopted method, which are reflected in the primary outcomes if they happen within the study period.[14]

Please see Appendix D for ethical considerations, which include IRB approvals, study registration, and protocols.

4 Results

4.1 Estimation strategy

We begin by presenting the impact of offering discounts for LARCs using:

$$Y_i = \alpha + \beta L_i^{Low} + \gamma L_i^{Mid} + \delta X_i + \epsilon_i \tag{1}$$

where Y_i denotes the outcome for client i. L_i denotes binary LARC price indicators for whether clients were offered LARCs at *Low* (CFA 150 or 0) or *Mid* prices (CFA 2,000 or 1,000), respectively. X_i denotes covariate adjustments, which, by design, only includes an indicator variable for SARCs

[12] We supplement these data with follow-up surveys of HGOPY clients, who were enrolled into the adaptive experiment that followed the pilot, within one to two weeks of their initial FP counseling session. We use these data to assess if service quality and client satisfaction differ by counseling approach.

[13] Survey evidence from the sample of clients enrolled in the ongoing adaptive experiment indicates that every client who adopted a method later, adopted it at HGOPY.

[14] Approximately 90% of clients, who have returned to HGOPY to adopt (or remove or switch) their chosen method, have done so within 100 days of their initial visit. Therefore, our data include clients whose initial visit was between 9 June 2020 and the 9 March 2021, who may have returned to HGOPY for a follow-up visit until 17 June 2021.

being offered for *free*. It is de-meaned and interacted with each treatment indicator, so that the estimated coefficients for LARC prices can be interpreted as the average treatment effects.[15]

We then present the effects of counseling and their interaction with discounts for LARCs by running the same regression model separately for MiM, IDM, and SDM. Tests of equality of means across IDM and SDM for each level of discount yield the causal effect of IDM on contraceptive take-up, compared to SDM.

Table 1: Impacts of price discounts for LARCs on method adoption.

	(1) **Adopted a LARC**	(2) **Adopted a SARC**	(3) **Adopted nothing**
LARC: Low	0.160	0.005	-0.165
	(0.048)	(0.024)	(0.049)
LARC: Mid	0.132	-0.032	-0.100
	(0.047)	(0.021)	(0.048)
High LARC price mean:	0.321	0.058	0.622
Difference: $\beta^{LARC}_{Low} - \beta^{LARC}_{Mid}$	0.027	0.037	-0.065
p-value	0.495	0.031	0.110
Obs.	784	784	784

Notes: Robust standard error in parentheses; Free/low price group were offered LARCs at CFA 0 or 150, Mid group at CFA 1,000 or 2,000, and the control group at CFA 4,000; column 1 shows the results of estimation on the likelihood of clients having adopted a LARC during the study period, column 2 a SARC, and column 3 neither a LARC nor a SARC; all columns show the base model with only the LARC and SARC price indicators centered and fully interacted so that coefficients on the main effects show average treatment effects.

4.2 Main results

Tables A2 and A3 show that client characteristics are balanced across randomly assigned LARC prices and counseling interventions, respectively. Table 1 presents the overall impacts of offering discounts for LARCs on our three primary outcomes, averaged over counseling conditions and SARC prices: at the highest price in our study, i.e. CFA 4,000, 32% of the clients adopt a LARC (column 1). Offering LARCs for free or at a very small price (CFA 150) increases LARC adoption by 16 pp - a 50% increase. Smaller discounts (CFA 2,000 or 1,000) are almost equally effective in increasing LARC uptake.[16] Discounts for LARCs do not affect the uptake of SARCs (column 2), which implies that the large gains in LARC uptake are mainly obtained from a similar reduction in the share of clients who would have left HGOPY having adopted no modern method (column 3).

[15] We treat the SARC price indicator as a covariate rather than a treatment variable, because, as explained in footnote 5, we discontinued randomizing clients to *free* or *full price* SARCs towards the end of the pilot period. Table A5 shows, in the sub-sample that received random SARC discounts, that offering SARCs for free had no discernible effect on the take-up of SARCs or LARCs - either directly or in interaction with discounts for LARCs.

[16] Tables A6-A8 assess the sensitivity of these findings. Examining the granular impact at each price level, including additional controls using a double selection lasso estimator, or adding fully-interacted month fixed effects do not alter the conclusions. Contrasting Table A7 with Table 1 reveals that the impacts grow in the days following the initial visit, during which time some clients, who had initially adopted no method or a SARC, return to adopt a LARC.

Figure 2 presents the heterogeneity of price effects across the three counseling regimes: (i) clients who stated that they have a method in mind and do not want to discuss any other methods (MiM); clients who have no method in mind (or have a SARC in mind but happy to discuss other methods) and are randomized into either (ii) *IDM* or (iii) *SDM*. For this analysis, we pool all discounted LARC prices into one *Discounted* group to maximize power.[17]

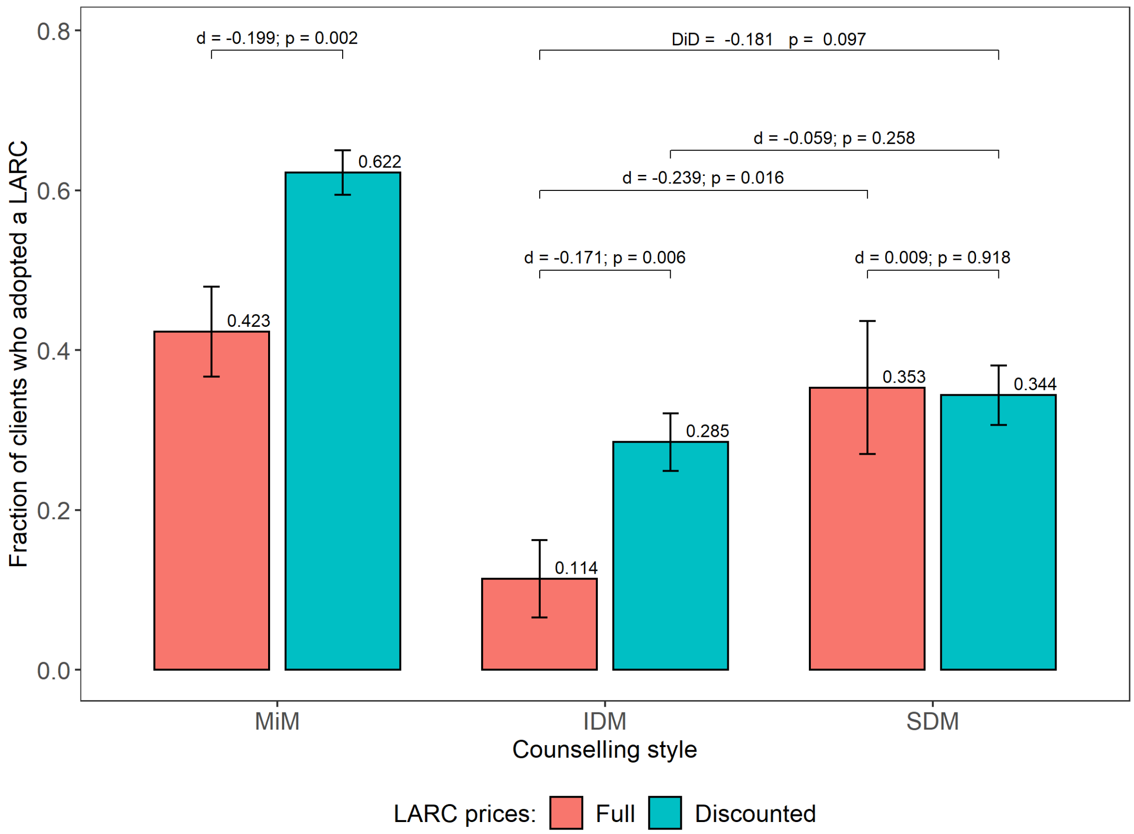


Figure 2: The figure shows the fraction of clients who adopted a LARC during the study period under *Discounted* and *Full* LARC prices across counseling styles. The lines above the bars show the estimate (d) and p-value (p) from a t-test of the difference in means between the two indicated groups. The bar labeled *DiD* indicates the difference-in-differences estimate between the two randomized counseling interventions (*IDM-SDM*) and LARC price discounts (*Full-Discounted*).

Among the clients with a method in mind (MiM), 42% adopt a LARC at the highest price and discounts for LARCs increase this share by 20 pp. Table A1 shows that MiM differs from other participants: they are older, more likely to be married, have higher levels of education, and want no more children. Among those who are unsure about the method they'd like to adopt, when clients are randomly assigned to *IDM*, only 11% of them adopt a LARC at full price. Receiving

[17]Table A9 presents impact estimates using the same specification as Table 1 for each counseling regime.

a discount, on average, increases this share to 29%. Under *SDM*, however, the uptake of LARCs at full price jumps to 35% - an increase of over 300% over *IDM*. Interestingly, *SDM* seems to also cause clients to become less sensitive to LARC prices: offering them discounts makes no difference to the adoption of LARCs. The difference in the effect of *Discounted* LARCs between *IDM* and *SDM* is 18.1 pp (p=0.097).

In Appendix Section C, we present a model of individual utility maximization, where the clients care about the price of LARCs and the perceived returns to adopting them. This model provides straightforward implications that is consistent with *SDM* causing a decline in the price elasticity of demand for LARCs. Importantly, follow-up surveys with clients indicate that this counseling approach maintained respect for their autonomy in decision-making: we found no differences between the two randomized counseling arms in a checklist of quality of service indicators, clients' level of satisfaction with their counseling session, or their willingness to return to the hospital for FP services in the future (Table A10).

4.3 Heterogeneity of impacts

In this sub-section, we ask, "What characterizes the client segment that is more likely to be persuaded by price discounts?" To answer this question, we first estimate the conditional average treatment effect (CATE) on LARC adoption of switching from *High* prices to *Low* or *Mid* prices (as in the previous section, we binarized the treatment by pooling all the discounted prices). Then, we say an individual is relatively "strongly" affected by discounts if their estimated CATE on LARC adoption is above the median estimated CATE in the data, and relatively "weakly" affected otherwise, where we hold out folds of data in estimating the CATE so that an individual's own outcome does not influence its subgroup assignment. We calculate the average treatment effect (ATE) for each subgroup. Finally, we compare the average value of each covariate of interest across the two subgroups. See, e.g., Chernozhukov et al. (2018, Section 3.2) or Athey and Wager (2019, Section 2.2) for similar methods.

We estimate the CATE non-parametrically by fitting three causal forests[18] (Athey et al., 2019). As our analysis in the previous section strongly suggests that individuals react differently to treatment depending on counseling regimes, we split our data into three separate subsets by counseling regime (*MiM*, *IDM* or *SDM*), and fit a separate causal forest for each subset. We then concatenated their predictions to compute the results in this section; this is essentially equivalent to forcing the trees to split by counseling regime. Details are provided in Appendix Section F.

The first row in Panel A of Table 2 presents the ATE of discounts on LARC adoption by subgroup. For the *strongly*-affected subgroup, we estimate an ATE of about 27 percentage points (pp), significant at the 1% level. Among those *weakly*-affected by discounts, we cannot distinguish the effect from zero. The difference in ATE between the two groups is significantly different than zero at the 1% level. The second row in Panel A estimates the subgroup-specific ATE using augmented inverse propensity scores (AIPW), cross-fitted so that an individual's outcome is not used to estimate the conditional mean or propensity score for themselves, enabling estimates with lower variance. The results are very similar across the two methods.

[18] Using the function `causal_forest` function implemented in the `R` package `grf`.

Table 2: Average treatment effect within each subgroup defined by ranking

	(1) **"Strong" group**	(2) **"Weak" group**	(3) **Difference**
Panel A: Average subgroup ATE			
Sample averages	0.268	0.021	0.246
	(0.059)	(0.061)	(0.084)
AIPW	0.255	0.029	0.226
	(0.056)	(0.057)	(0.080)
Panel B: Average subgroup ATE by counselling style			
SDM	-	-0.009	-
		(0.091)	
MiM	0.269	0.043	0.226
	(0.073)	(0.117)	(0.138)
IDM	0.246	0.086	0.160
	(0.081)	(0.090)	(0.121)

Notes: "Strong" and "weak" refer to subgroups whose conditional average treatment effect (CATE) of switching from *High* to *Discounted* (i.e., *Low* or *Mid*) prices is above (strong) or below (weak) the median CATE estimate in the data; Panel A shows estimates for the entire sample and Panel B shows estimates per counselling style. The ATE estimates in Panel B are sample averages.

Panel B of Table 2 further subdivides the sample depending on counseling assignment. Consistent with the analysis in the previous subsection, we find that clients receiving *SDM* are all classified by the causal forest as weakly affected. Meanwhile, the "strong" group contains clients from both the *MiM* and *IDM* groups, and each of these subgroups show a positive and significant effect of discounts.

Table 3 characterizes clients in each subgroup. Clients who are strongly affected by discounted LARC prices are substantially younger than weakly-affected clients. Consequently, they are more likely to be students, to want to delay pregnancy by at least three years, and to want more children in the future. They also have higher levels of education and are more likely to present at the FP department to seek counseling. Figure B1 in the appendix presents LARC adoption rates under *High* and *Discounted* prices for each counseling regime by individual client characteristics. The patterns are consistent with Table 3.

Table 3: Average covariate per data-driven subgroup (grf-based model).

	(1) **"Strong" group**	(2) **"Weak" group**	(3) **Difference**
Age	27.025	31.546	-4.521
	(0.279)	(0.386)	[0.000]
Cohabiting	0.378	0.362	0.017
	(0.024)	(0.024)	[0.699]
Married	0.302	0.367	-0.065
	(0.023)	(0.024)	[0.097]
Single	0.320	0.272	0.048
	(0.024)	(0.023)	[0.228]
Family Planning	0.650	0.492	0.157
	(0.024)	(0.025)	[0.000]
Education [Primary]	0.086	0.174	-0.088
	(0.014)	(0.019)	[0.001]
Education [Secondary]	0.492	0.405	0.087
	(0.025)	(0.025)	[0.029]
Education [Tertiary]	0.421	0.421	0.001
	(0.025)	(0.025)	[0.982]
Spacing [1-3 yrs or unsure]	0.353	0.369	-0.016
	(0.024)	(0.024)	[0.699]
Spacing [3+ yrs]	0.480	0.290	0.190
	(0.025)	(0.023)	[0.000]
Spacing [No more children]	0.168	0.341	-0.174
	(0.019)	(0.024)	[0.000]
Occupation [Salaried]	0.332	0.344	-0.011
	(0.024)	(0.024)	[0.780]
Occupation [Domestic]	0.206	0.241	-0.035
	(0.020)	(0.022)	[0.351]
Occupation [Self-employed]	0.195	0.221	-0.025
	(0.020)	(0.021)	[0.479]
Occupation [Student]	0.266	0.195	0.072
	(0.022)	(0.020)	[0.033]
Children	2.421	3.079	-0.658
	(0.079)	(0.100)	[0.000]
Modern contraceptive	0.061	0.079	-0.019
	(0.012)	(0.014)	[0.406]
Ideal num. of children	2.558	1.956	0.602
	(0.091)	(0.096)	[0.000]
Counselling style [MiM]	0.726	0.254	0.472
	(0.023)	(0.022)	[0.000]
Counselling style [IDM]	0.274	0.241	0.033
	(0.023)	(0.022)	[0.406]
Counselling style [SDM]	0.000	0.505	-0.505
	(0.000)	(0.025)	[0.000]

Notes: *Strong* and *Weak* refer to subgroups whose conditional average treatment effect (CATE) when switching from zero to positive discounts. A positive number in the "Difference" column indicates that the average covariate value for the "strong" subgroup is higher. Standard errors in parenthesis. P-values for the difference between groups shown in square brackets (using Benjamini-Hochberg correction for multiple hypothesis testing).

5 Concluding discussion

We conducted a randomized experiment to tackle two main barriers to the uptake of contraceptives: credit constraints and information. Offering discounts was very effective in increasing LARC adoptions, particularly among younger, unmarried clients. Clients presenting in the maternity or the gynecology ward, most of whom had recently given birth, also responded strongly to low prices for LARCs (Table A11). While increasing demand for LARCs by reaching more women outside health care settings is surely important, current clients of clinics represent an important opportunity. Checklists for antenatal visits, childhood vaccinations, postpartum and post-abortion clients should all include an item to ask whether the client is using an effective contraceptive method and, if not, whether she would like a brief counseling session (accompanied with improved and discounted services). Our findings are consistent with recent evidence on the effect of price reductions in increasing the uptake of LARCs. They are also consistent with the use of incentives to increase the take-up of other preventive health measures, such as immunizations in India (Banerjee et al., 2021) or male circumcisions in South Africa (Friedman and Wilson, 2021).

Counseling clients with the shared decision-making approach (*SDM*) substantially increased the adoption of LARCs at full price. In fact, *SDM* was so effective in raising willingness-to-pay for LARCs that offering discounts to these clients did not further increase adoption. This is particularly striking given the relatively minor differences between *SDM* and *IDM*: in both cases the client can choose (or decline) to discuss one method in more detail first, followed by other methods until she decides. The only variation is in whether or not the *app* suggests an initial order of discussion. This tweak caused increases in LARC uptake that were as large as the effect of providing these methods for *free* under *IDM*. As such, we not only show that LARC uptake can be substantially increased within a comprehensive framework for high-quality counseling (Holt et al., 2017), but also that such a shift might be cost-effective in preventing unintended pregnancies without causing any trade-offs in client satisfaction or autonomy.

Finally, the heterogeneity analysis suggests that unmarried adolescents may be highly motivated to avoid unintended pregnancies and are responsive to low prices. For example, clients who respond strongly to discounts for LARCs are more likely to be students than those who respond weakly. Campaigns to reach adolescent girls and young women might be successful if they can combine high-quality counseling with affordable prices and convenient (and discreet) opportunities to adopt. This is consistent with recent evidence, also from Cameroon, which showed that providing sexual and reproductive health information to adolescents at school can decrease the incidence of teenage pregnancies (Dupas et al., 2018).

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A Appendix tables

Table A1: Client characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Full sample	**Department**			**Method in Mind**		
		FP	**Mat./Gyn.**	Diff.	**Yes**	**No**	Diff.
	Mean/(SD)	Mean/(SD)	Mean/(SD)	(p-value)	Mean/(SD)	Mean/(SD)	(p-value)
Age	29.27(7.03)	29.64(7.05)	28.78(6.98)	0.09	30.33(6.77)	28.26(7.13)	0.00
Adolescent	0.09	0.07	0.10	0.10	0.05	0.12	0.00
BMI	27.52(4.86)	27.44(4.97)	27.63(4.71)	0.58	27.58(5.03)	27.47(4.69)	0.75
Single	0.30	0.27	0.33	0.09	0.23	0.36	0.00
Unmarried couple cohabiting	0.37	0.33	0.41	0.02	0.36	0.38	0.47
Married	0.33	0.39	0.26	0.00	0.41	0.26	0.00
Education: Tertiary	0.42	0.47	0.35	0.00	0.46	0.38	0.01
Education: Secondary	0.23	0.22	0.24	0.56	0.22	0.25	0.32
Education: Primary/Lower sec.	0.33	0.29	0.38	0.00	0.30	0.35	0.12
Education: None	0.02	0.02	0.02	0.94	0.02	0.02	0.67
Salaried employee	0.32	0.34	0.28	0.08	0.37	0.27	0.00
Self-employed	0.21	0.19	0.24	0.10	0.21	0.21	0.99
Student or apprentice	0.23	0.22	0.24	0.56	0.18	0.28	0.00
Domestic activities	0.22	0.23	0.21	0.39	0.22	0.23	0.87
Pregnancies, total	3.69(2.33)	3.65(2.32)	3.74(2.35)	0.60	4.01(2.29)	3.39(2.33)	0.00
Children alive today	2.75(1.81)	2.73(1.80)	2.78(1.83)	0.68	3.01(1.78)	2.50(1.81)	0.00
Ever gave birth (live or still)	0.94	0.94	0.94	0.86	0.95	0.93	0.17
Gave birth $\leq$3 months	0.56	0.34	0.84	0.00	0.44	0.67	0.00
Wants no more children	0.25	0.24	0.27	0.34	0.30	0.21	0.00
Wait 1 to 3 yrs before next preg.	0.36	0.36	0.36	0.97	0.29	0.43	0.00
Wait >3 years before next preg.	0.39	0.40	0.37	0.42	0.41	0.36	0.20
Currently using a LARC	0.03	0.05	0.01	0.00	0.06	0.01	0.00
Currently using a SARC	0.04	0.05	0.02	0.01	0.04	0.03	0.30
Currently using other method	0.05	0.08	0.01	0.00	0.07	0.03	0.01
N	784	448	336		385	399	

Note: This table shows client characteristics in the full sample and by department; column 1 includes the full sample of clients; columns 2 includes clients who received a consultation at the family planning department, i.e. who visited the family planning unit through their own personal initiative; column 3 includes clients who visited another hospital department, primarily maternity and gynecology, and were referred for a family planning consultation; column 4 shows the p-value from a t-test of the difference in means between columns 2 and 3.

Table A2: Balance table over LARC prices

	(1) Control	(2) LARC price: Mid	(3)	(4) LARC price: Low	(5)
	Mean/(SD)	Mean/(SD)	Diff 1-2 (p-value)	Mean/(SD)	Diff 1-4 (p-value)
Dep.: Family Planning	0.59	0.57	0.76	0.56	0.52
Age	28.79/(7.44)	29.40/(7.08)	0.39	29.38/(6.74)	0.40
Adolescent	0.10	0.09	0.73	0.07	0.20
BMI	27.32/(4.92)	27.26/(4.88)	0.89	27.93/(4.79)	0.21
Single	0.35	0.29	0.19	0.28	0.14
Unmarried couple cohabiting	0.34	0.37	0.54	0.38	0.35
Married	0.31	0.34	0.51	0.33	0.68
Education: Tertiary	0.38	0.40	0.73	0.46	0.11
Education: Secondary	0.27	0.21	0.17	0.23	0.37
Education: Primary/Lower sec.	0.35	0.36	0.83	0.29	0.19
Education: None	0.00	0.03	0.03	0.02	0.07
Salaried employee	0.27	0.34	0.11	0.31	0.34
Self-employed	0.19	0.19	0.88	0.24	0.20
Student or apprentice	0.26	0.21	0.19	0.24	0.56
Domestic activities	0.26	0.24	0.63	0.19	0.10
Pregnancies, total	3.66/(2.45)	3.74/(2.34)	0.74	3.65/(2.26)	0.98
Children alive today	2.63/(1.80)	2.90/(1.88)	0.13	2.64/(1.72)	0.93
Ever gave birth (live or still)	0.94	0.95	0.55	0.93	0.77
Wants no more children	0.22	0.28	0.21	0.24	0.68
Wait 1 to 3 yrs before next preg.	0.40	0.33	0.12	0.37	0.49
Wait >3 years before next preg.	0.37	0.39	0.71	0.39	0.74
Currently using a LARC	0.03	0.04	0.30	0.02	0.90
Currently using a SARC	0.03	0.03	0.96	0.04	0.53
Currently using other method	0.03	0.07	0.10	0.04	0.64
Method in mind	0.50	0.47	0.58	0.51	0.89
Test of joint orthogonality, F-stat		0.88		1.04	
p-value		0.62		0.41	
N	156	334		294	

Note: the ‘Difference’ columns show the p-value from a t-test of the difference in means between the two indicated groups; the F-test of joint-orthogonality (F-stat/p-value) tests that all the coefficients are jointly equivalent to zero when regressing the set of variables shown in this table on a group indicator; Standard deviation in parentheses for non-binary variables.

Table A3: Balance table over the counselling style

	(1) SBS	(2) SEQ	(3)
	Mean/(SD)	Mean/(SD)	Diff. (p-value)
Dep.: Family Planning	0.50	0.48	0.65
Age	28.67/(7.06)	27.84/(7.18)	0.24
Adolescent	0.11	0.12	0.69
BMI	27.49/(4.69)	27.45/(4.71)	0.93
Single	0.33	0.39	0.18
Unmarried couple cohabiting	0.40	0.37	0.53
Married	0.28	0.24	0.45
Education: Tertiary	0.39	0.37	0.75
Education: Secondary	0.28	0.21	0.14
Education: Primary/Lower sec.	0.32	0.39	0.12
Education: None	0.02	0.03	0.71
Salaried employee	0.28	0.25	0.60
Self-employed	0.20	0.22	0.62
Student or apprentice	0.28	0.27	0.86
Domestic activities	0.21	0.24	0.54
Pregnancies, total	3.42/(2.38)	3.35/(2.28)	0.76
Children alive today	2.61/(1.84)	2.39/(1.77)	0.23
Ever gave birth (live or still)	0.94	0.92	0.52
Wants no more children	0.19	0.23	0.39
Wait 1 to 3 yrs before next preg.	0.45	0.40	0.32
Wait >3 years before next preg.	0.36	0.37	0.77
Currently using a LARC	0.00	0.01	0.15
Currently using a SARC	0.03	0.03	0.96
Currently using other method	0.02	0.04	0.22
Test of joint orthogonality, F-stat			0.93
p-value			0.56
N	202	197	

Note: the ‘Difference’ columns show the p-value from a t-test of the difference in means between the two indicated groups; the F-test of joint-orthogonality (F-stat/p-value) tests that all the coefficients are jointly equivalent to zero when regressing the set of variables shown in this table on a group indicator; Standard deviation in parentheses for non-binary variables.

Table A4: Method mix.

	(1)	(2)	(3)	(4)	(5)	(6)
	Current method		**Method in mind**		**Method adopted**	
	N	%	N	%	N	%
None	**689**	**87.88**	**342**	**43.62**	**237**	**30.23**
LARC	**26**	**3.32**	**358**	**45.66**	**342**	**43.62**
IUD	3	0.38	99	12.63	101	12.88
Implant	23	2.93	259	33.04	241	30.74
SARC	**29**	**3.70**	**62**	**7.91**	**35**	**4.46**
Pill	11	1.40	18	2.30	17	2.17
Injectable	18	2.30	44	5.61	18	2.30
Other	**40**	**5.10**	**22**	**2.81**	**170**	**21.68**
LAM	1	0.13	5	0.64	153	19.52
Male/Female condoms	36	4.59	8	1.02	12	1.53
Traditional or other	3	0.38	9	1.15	5	0.64
Total	**784**	**100.00**	**784**	**100.00**	**784**	**100.00**

Note: This table shows the method mix amongst the clients who visit the hospital included in the study sample; columns 1 and 2 show the number and fraction of clients who are currently using each method at the time of their first consultation; columns 2 and 3 shows which method the 442 clients had in mind during their consultation, i.e. the method they wanted to adopt or renew without discussing other methods (see Figure 1); column 5 and 6 show the method that was ultimately adopted by the clients, noting that LAM and condoms can be used concurrently with other methods and are thus counted as the method adopted when they are used as the primary method of contraception; the IUD refers to the copper IUD, LAM refers to lactational amenorrhea method, traditional method or other encompasses all other methods and primarily consists of the calendar method and coitus interruptus method.

Table A5: Impacts of price discounts on method adoption, fully randomized prices sample.

	(1) **Adopted a LARC**	(2) **Adopted a SARC**	(3) **Adopted nothing**
LARC: Low	0.172	-0.013	-0.159
	(0.053)	(0.028)	(0.055)
LARC: Mid	0.166	-0.051	-0.115
	(0.054)	(0.026)	(0.056)
SARC: Free	0.046	-0.009	-0.037
	(0.039)	(0.017)	(0.040)
LARC: Low X SARC: Free	0.071	-0.032	-0.038
	(0.106)	(0.057)	(0.110)
LARC: Mid X SARC: Free	0.028	0.008	-0.036
	(0.107)	(0.052)	(0.111)
High LARC price mean:	0.301	0.071	0.628
Difference: $\beta^P_{Low} - \beta^P_{Mid}$	0.006	0.038	-0.044
p-value	0.894	0.028	0.324
Obs.	627	627	627

Notes: Robust standard error in parentheses; Free/low price group were offered LARCs at CFA 0 or 150, Mid group at CFA 1,000 or 2,000, and the control group at CFA 4,000; all models are estimated limiting the sample to the period where SARC prices were fully randomized (i.e. before January 20^{th}, see section 2.2.1); column 1 shows the results of estimation on the likelihood of clients having adopted a LARC during the study period (i.e. the IUD of the implant), column 2 on the likelihood of clients having adopted a SARC (i.e. the injectable or the pill), and column 3 on the likelihood of having adopted neither a LARC nor a SARC; all columns show the base model with only the LARC and SARC price indicators all centered and fully interacted with each other so that coefficients on the main effects can be interpreted as the ATE.

Table A6: Impacts of price discounts on method adoption, full set of price indicators.

	(1) **Adopted a LARC**	(2) **Adopted a SARC**	(3) **Adopted nothing**
LARC: Free	0.204	-0.015	-0.189
	(0.054)	(0.025)	(0.055)
LARC: 150	0.090	0.033	-0.124
	(0.058)	(0.033)	(0.060)
LARC: 1000	0.162	-0.036	-0.126
	(0.054)	(0.022)	(0.055)
LARC: 2000	0.100	-0.027	-0.073
	(0.055)	(0.024)	(0.056)
High LARC price mean:	0.321	0.058	0.622
Tests of equality of coefficients:			
0=150	0.053	0.123	0.275
0=1000	0.443	0.287	0.248
0=2000	0.063	0.575	0.038
150=1000	0.216	0.018	0.972
150=2000	0.862	0.047	0.402
1000=2000	0.262	0.617	0.341
Obs.	784	784	784

Notes: Robust standard error in parentheses; column 1 shows the results of estimation on the likelihood of clients having adopted a LARC during the study period (i.e. the IUD of the implant), column 2 on the likelihood of clients having adopted a SARC (i.e. the injectable or the pill), and columns 3 on the likelihood of having adopted neither a LARC nor a SARC during the study period (condoms and LAM are not counted); all models include only LARC and SARC price indicators centered and fully-interacted so that coefficients on the main effects can be interpreted as the ATE.

Table A7: Impacts of price discounts on method adoption after the first consultation.

	(1) **Adopted a LARC**	(2) **Adopted a SARC**	(3) **Adopted nothing**
LARC: Low	0.104	0.019	-0.123
	(0.047)	(0.021)	(0.048)
LARC: Mid	0.081	-0.011	-0.071
	(0.046)	(0.018)	(0.047)
High LARC price mean:	0.301	0.038	0.660
Difference: $\beta^P_{Low} - \beta^P_{Mid}$	0.022	0.030	-0.052
p-value	0.575	0.075	0.195
Obs.	784	784	784

Notes: Robust standard error in parentheses; Free/low price group were offered LARCs at CFA 0 or 150, Mid group at CFA 1,000 or 2,000, and the control group at CFA 4,000; column 1 shows the results of estimation on the likelihood of clients having adopted a LARC during the study period (i.e. the IUD of the implant), column 2 on the likelihood of clients having adopted a SARC (i.e. the injectable or the pill), and column 3 on the likelihood of having adopted neither a LARC nor a SARC; all columns show the base model with only the LARC and SARC price indicators centered and fully interacted with each other so that coefficients on the main effects can be interpreted as the ATE.

Table A8: Impacts of price discounts on method adoption, robustness.

	(1)	(2)	(3)	(4)	(5)	(6)
	Adopted a LARC		**Adopted a SARC**		**Adopted nothing**	
	DS Lasso	Month FE	DS Lasso	Month FE	DS Lasso	Month FE
LARC: Low	0.188	0.194	0.010	0.007	-0.193	-0.201
	(0.044)	(0.048)	(0.025)	(0.024)	(0.043)	(0.049)
LARC: Mid	0.164	0.146	-0.033	-0.032	-0.133	-0.114
	(0.042)	(0.046)	(0.021)	(0.020)	(0.041)	(0.048)
High LARC mean:	0.321	0.321	0.058	0.058	0.622	0.622
Diff.: $\beta^P_{Low} - \beta^P_{Mid}$	0.024	0.048	0.043	0.039	-0.060	-0.087
p-value	0.539	0.238	0.018	0.036	0.109	0.030
Obs.	784	784	784	784	784	784
Lasso sel. controls	Yes	No	Yes	No	Yes	No
Num. sel. controls	3	-	4	-	5	-
Month FE	No	Yes	No	Yes	No	Yes

Notes: Robust standard error in parentheses; Free/low price group were offered LARCs at CFA 0 or 150, Mid group at CFA 1,000 or 2,000, and the control group at CFA 4,000; columns 1-2 show the results of estimation on the likelihood of clients having adopted a LARC during the study period (i.e. the IUD of the implant), columns 3-4 on the likelihood of clients having adopted a SARC (i.e. the injectable or the pill), and columns 5-6 on the likelihood of adopting neither a LARC nor a SARC; columns 1, 3, and 5 shows the baseline model estimated using a double selection lasso estimator which selects additional controls from a large set of available variables as in Belloni et al. 2014, all controls are centered and fully interacted with LARC and SARC price indicators; columns 2, 4 and 6 show the base model with a set of month fixed effects added, all centered and fully interacted with LARC and SARC price indicators.

Table A9: Impacts of price discounts on LARC and SARC adoptions by counselling style.

	(1)	(2)	(3)	(4)	(5)	(6)
	Adopted a LARC			**Adopted a SARC**		
	MiM	IDM	SDM	MiM	IDM	SDM
LARC price: Free/Low	0.220	0.180	0.023	–0.010	0.000	0.029
	(0.071)	(0.077)	(0.097)	(0.042)	(0.039)	(0.034)
LARC price: Mid	0.198	0.178	0.005	–0.062	0.000	-0.011
	(0.070)	(0.067)	(0.096)	(0.037)	(0.036)	(0.025)
High price mean	0.423	0.114	0.353	0.077	0.045	0.029
Low=Mid w/n group	0.699	0.975	0.805	0.043	0.998	0.156
Low=Low b/w group (p-val.)		0.205			0.577	
Mid=Mid b/w groups (p-val.)		0.140			0.807	
High=High b/w groups (p-val.)		0.020			0.585	
Obs. in group	385	202	197	385	202	197
Obs.		784			784	

Notes: Robust standard error in parentheses; Free/low price group were offered LARCs at CFA 0 or 150, Mid group at CFA 1,000 or 2,000, and the control group at CFA 4,000; columns 1-3 show the marginal effects of offering discounts for LARCs within each counselling style group on the likelihood of adopting a LARC, estimated using one regression where the baseline model is fully interacted with the IDM and SDM counselling style indicators; columns 4-6 show these same results on the likelihood of adopting a SARC; columns 1 and 4 show the impact for clients with a method in mind and columns 2 and 5, and 3 and 6, for clients randomized into the IDM and SDM groups, respectively; all regressions include an indicator for Free SARCs centered and fully interacted with LARC prices; tests indicated as w/n group test the equality of the Low and Mid price coefficients *within* the counselling style group, and between group tests test the equality of coefficients *between* the IDM and SDM groups.

Table A10: Quality of care and client satisfaction by consultation style.

	(1) **Status-Quo** Mean	(2) **Recommendation** Mean	(3) Diff. p-value
Variable	Mean/SD	Mean/SD	(1)-(2)
Quality of care index	0.70	0.69	0.85
Domain specific indices			
Audio and visual privacy	0.25	0.21	0.48
Method selection	0.88	0.90	0.53
Effective use	0.84	0.87	0.50
Continuity of care	0.80	0.77	0.67
Client satisfaction			
Fraction satisfied with FP services in general	0.87	0.87	0.92
Fraction satisfied with FP consultation	0.97	0.96	0.71
Fraction likely to return for FP services	0.95	0.94	0.96

Note: The data shown in this table covers a sample of clients enrolled between 19^{th} of January and 28^{th} of June, 2021. The 'Difference' columns show the p-value from a t-test of the difference in means between the two indicated groups. The quality of care domain indices are calculated following Jain et al. (2019) by averaging the components within each domain; the quality of care index is obtained by averaging across the four domain specific indices so that each domain is equally weighted; the audio and visual privacy index reflects the respectful care domain from Jain et al; measures of satisfaction indicate the fraction of clients who are satisfied, or very satisfied with FP services and general and with the FP consultation specifically, as well as the clients who are likely, or very likely to return to the study hospital for FP services in the future.

Table A11: Heterogeneity of impacts of price discounts.

	(1)	(2)	(3)	(4)	(5)	(6)
	Department		**Age group**		**Method in mind**	
	FP	Mat./Gyn.	Age≥20	Age<20	No MiM	MiM
Panel A: Adopted a LARC						
LARC price: Free/Low	0.134	0.212	0.135	0.425	0.106	0.215
	(0.065)	(0.067)	(0.050)	(0.139)	(0.061)	(0.069)
LARC price: Mid	0.192	0.050	0.109	0.294	0.089	0.185
	(0.062)	(0.062)	(0.049)	(0.122)	(0.058)	(0.068)
Control mean w/n group	0.402	0.203	0.343	0.125	0.218	0.423
Low=Mid w/n group (p-val.)	0.280	0.004	0.534	0.360	0.741	0.589
Low=Low b/w groups (p-val.)	0.401		0.051		0.239	
Mid=Mid b/w groups (p-val.)	0.110		0.159		0.288	
Panel B: Adopted nothing						
LARC price: Free/Low	–0.145	-0.212	-0.140	-0.412	-0.116	-0.211
	(0.065)	(0.068)	(0.051)	(0.147)	(0.064)	(0.068)
LARC price: Mid	–0.141	-0.049	-0.082	-0.232	-0.079	-0.133
	(0.063)	(0.064)	(0.051)	(0.132)	(0.061)	(0.069)
Control mean w/n group	0.511	0.781	0.600	0.813	0.744	0.500
Low=Mid w/n group (p-val.)	0.939	0.005	0.163	0.202	0.490	0.143
Low=Low b/w groups (p-val.)	0.474		0.081		0.307	
Mid=Mid b/w groups (p-val.)	0.304		0.290		0.556	
Obs. in group	448	336	717	67	399	385
Obs.	784		784		784	

Notes: Robust standard error in parentheses; Free/low price group were offered LARCs at CFA 0 or 150, Mid group at CFA 1,000 or 2,000, and the control group at CFA 4,000; all sets of columns show the estimated coefficients for the group-specific impacts of LARC prices estimated from a single regression on the outcome on LARC prices interacted with a group indicator; regressions shown in columns 1 and 2 report results from interacting LARC prices with the department where the client was received as the group indicator, separated as Family Planning and Maternity/Gynecology+others; regressions in columns 3 and 4 use an indicator for the age group; regressions in columns 5 and 6 use an indicator whether the client had a method in mind, i.e. already knew which method they wanted to adopt or renew and did not want to discuss other methods (see Figure 1).

B Appendix figures

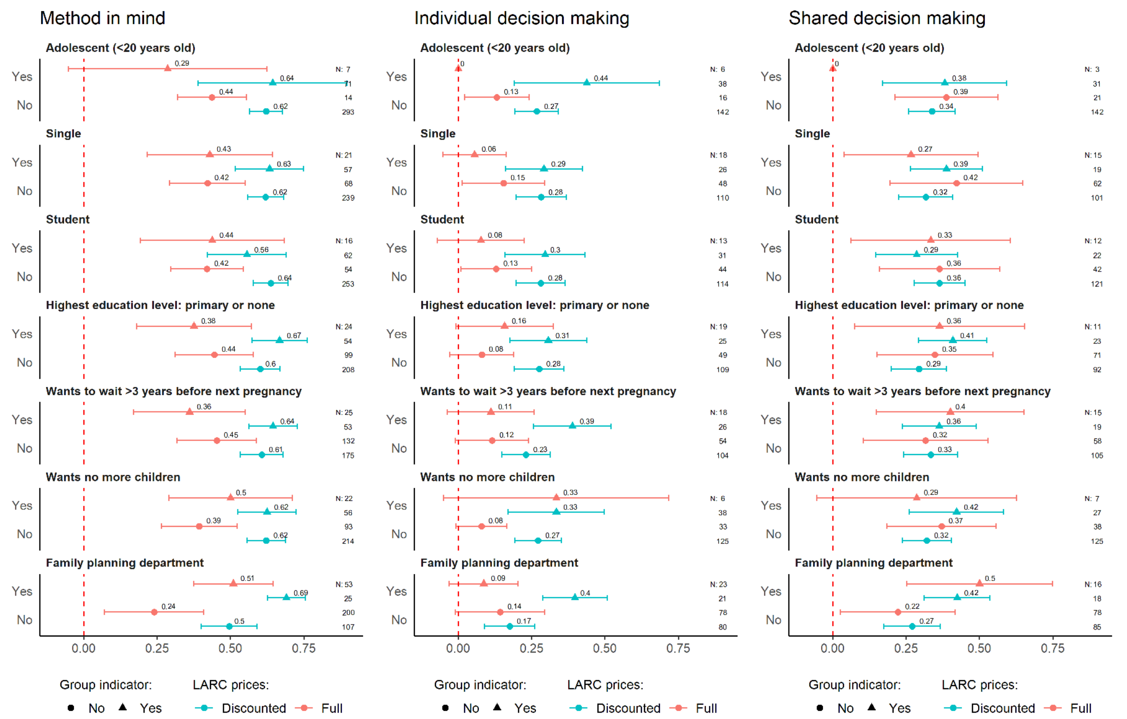

Figure B1: This figure shows the mean LARC adoptions and 95%CI per client characteristics and price groups under each of the three counseling regimes.

C A Simple Model for the Price Effects of LARCs

An individual has utility over consumption, c, and her method of contraception: $u(c, ql + q_n(1-l))$, where $l \in \{0, 1\}$ denotes whether or not the individual uses a LARC, q denotes the perceived return to using the LARC, and q_n denotes the perceived return to using a non-modern contraceptive (for simplicity, we assume the individual believes she will get these returns with certainty). Implicitly, we assume that, in the absence of the LARC, the individual will always prefer to use the non-modern contraceptive over an alternative method of contraception, i.e., SARCs. This seems reasonable in this setting given the very low uptake of SARCs. The individual solves:

$$\max_{l=\{0,1\}} u(c, ql + q_n(1-l))$$
$$\text{s.t. } c + pl \leq y$$

where p denotes the (relative) price of the LARC and y denotes the individual's income.[19] Assume for simplicity that $(q_n, y) \in R^2_+$ are both homogeneous (this can easily be relaxed), but that q is heterogeneous. In particular, assume the CDF of q takes the following form:

$$F(q) = \begin{cases} m & \text{if } q \in [0, \underline{q}) \\ (1-m)F_+(q) + m & \text{if } q \geq \underline{q} \\ 0 & \text{otherwise} \end{cases}$$

where $\underline{q} > 0$, $m \in (0, 1)$, and where F_+ denotes the smooth, increasing CDF for those individuals with positive, perceived returns $q \in [\underline{q}, \infty)$.[20] In words, there is a mass m of people who have a perceived return of 0 for the LARC and will therefore never choose the LARC for any (weakly) positive price.

Denote $\tilde{q}(p)$ as the perceived return that makes an individual just indifferent between choosing the LARC at price p over the non-modern contraceptive. Implicitly, $\tilde{q}(p)$ solves:

$$u(y - p, \tilde{q}) = u(y, q_n)$$

Assuming utility is increasing in the perceived quality of contraception, we know that those with $q > \tilde{q}(p)$ will choose a LARC at price p. We can then express the share of individuals choosing the LARC, S, as:

$$S = \int_{\tilde{q}(p)} dF(q) = 1 - F(\tilde{q}(p))$$

[19] We assume the non-modern method of contraception is free, although this can easily be relaxed.

[20] Assume that $\lim_{(q \to \underline{q})^+} f_+(q) = 0$ so that the density is continuous at $\underline{q}$.

We now derive how the share of individuals choosing the LARC changes as we raise the price of the LARC, i.e., we derive the "price effect" for the LARC (to obtain the elasticity, just multiply by p/S):

$$\frac{\partial S}{\partial p} = \begin{cases} -\frac{\partial \tilde{q}(p)}{\partial p} f_{+}\left(\tilde{q}(p)\right)(1-m) & \text{if } \tilde{q} > \underline{q} \\ 0 & \text{if } \tilde{q} \leq \underline{q} \end{cases}$$

where $-\frac{\partial \tilde{q}(p)}{\partial p} f_{+}(\tilde{q})(1-m) = -\frac{u_c(y-p,\tilde{q})}{u_q(y-p,\tilde{q})} f_{+}(\tilde{q})(1-m) < 0$ provided that utility is increasing in consumption and the perceived quality of contraception. Thus, as expected, we see that lowering the price of LARCs (weakly) increases the share of individuals taking-up the LARC.

Now consider the *SDM* counseling intervention (relative to the *IDM* intervention). We choose to model this intervention as increasing everyone's perceived return to LARCs by a factor of $\gamma > 1$ (note that a LARC was ranked as the most suitable method for the client 88% of the time under *SDM*, suggesting that this is a reasonable way to model this intervention relative to *IDM*). Thus, assuming the distribution of perceived returns under *IDM* is given by F, the distribution of perceived returns under *SDM* is given by:

$$G(q) = \begin{cases} m & \text{if } q \in [0, \gamma\underline{q}) \\ (1-m)F_{+}\left(\frac{q}{\gamma}\right) + m & \text{if } q \geq \gamma\underline{q} \\ 0 & \text{otherwise} \end{cases}$$

And the "price effect" under *SDM* is given by:

$$\frac{\partial S}{\partial p} = \begin{cases} -\frac{\partial \tilde{q}(p)}{\partial p} \frac{1}{\gamma} f_{+}\left(\frac{\tilde{q}(p)}{\gamma}\right)(1-m) & \text{if } \tilde{q} > \gamma\underline{q} \\ 0 & \text{if } \tilde{q} \leq \gamma\underline{q} \end{cases}$$

Thus, based on this framework, the only way we can observe a **positive** price effect when reducing the LARC price from the highest level under *IDM*, but a **zero** price effect under *SDM* is if $\underline{q} < \tilde{q}(p_{high}) \leq \gamma\underline{q}$, where p_{high} is the highest price charged for the LARC. In words, counseling clients under *SDM* must have shifted the distribution of perceived returns of LARCs sufficiently far to the right (i.e., $\gamma >> 1$) that, even under the highest price charged for the LARC, we reached maximum take-up of the LARCs. Therefore, offering discounts had no further effect on take-up once they were counseled under *SDM*.

D Ethical considerations

The study protocols were approved by Cameroon's National Ethics Committee for Human Subjects Research, the Comité National d'Ethique de la Recherche pour la Santé Humaine (CNERSH; decision No. 2019/08/1183/CE/CNERSH/SP). The study also received administrative authorization from the Ministry of Health's (MinSanté) Division of Health Operations Research (DROS; decision No. D30-760/L/MINSANTE/SG/DROS). Finally, the protocols were also approved by HGOPY's own IRB (decision No. 780/CIERSH/DM/2018). The adaptive experiment, for which the current study served as the pilot phase, is registered at the AEA RCT Registry and can be accessed here. Study protocols submitted for ethics review are included in the registration, which cover the full set of study procedures, including, but not limited to, data management and information security, enrollment criteria, consent procedures, and treatment of adverse reactions.

E The job-support tool

E.1 What does tablet-based job-support tool do?

The structure of the counselling session as guided by the job-support tool is not fundamentally different than the standard practice –worldwide and at HGOPY. In other words, the tool does not require any new knowledge or training on part of the provider. It simply is a job-aid that allows her to conduct the counseling session more efficiently. The process of family planning counselling using the job-support tool consists of three main sections, as such:

1. Introduction:
    (a) Welcome the client, explain the purpose of the session (talk about her life and goals, healthy families, pregnancy spacing, safe sex, and contraceptive methods), and clarify that the session is private and confidential.
    (b) Collect basic demographic information (age, marital status, education, primary activity, religion, and neighbourhood)
    (c) Discuss client's plans for having children in the future, how long she would like to wait before getting pregnant, how many more children she would like to have, and healthy birth spacing
    (d) Cover her birth history and establish her breastfeeding status
    (e) Conduct a pregnancy check
2. Consultation and needs assessment:
    (a) Discuss current method of birth control used by the client, if any. Discuss her experience with the method, how long she has been using it, and assess whether she would like to continue or switch

(b) Discuss any methods that she might be worried about. Any methods she has in mind that she is curious about.

(c) Clarify any questions or misconceptions the client might have about any contraceptive methods

(d) Ask her about her preferences regarding side effects concerning:

    i. Increased bleeding and cramping,

    ii. Decreased bleeding, spotting, and amenorrhea, and

    iii. Weight gain

(e) Obtain her medical history to avoid the adoption of contra-indicated methods. Take blood pressure and measure the height and weight of the client.

3. Method choice and follow-up:

    (a) Depending on the intervention condition, either ask the client to choose the modern method she would like to discuss first OR ask her whether she would like to discuss the method that is recommended by the tool as being the most suitable for her needs. When the client makes her choice as to which method she would like to discuss, the provider presents neutral, evidence-based, and understandable information on the effectiveness and the side effects of that method with the help of printed and laminated cue cards (see Appendix section E.4 for an example cue card).

    (b) Answer client's questions and concerns about the method being discussed. Listen to the client carefully and counsel her individually, based on her needs assessment.

    (c) Ask the client whether she would like to adopt the method or discuss another method. Discuss next preferred method, and so on, until the client decides to adopt or leave with no method.

    (d) Adoption of chosen method, as appropriate, along with documentation of consent for adopting a modern method, such as the pill, injectable, implant, or IUD.

    (e) Provide information on method use and follow-up mechanisms for switching or discontinuing selected method.

4. Conclusion:

    (a) Discuss the importance of dual protection from sexually transmitted diseases and provide the client with a package of condoms.

    (b) Schedule the next appointment, as appropriate.

    (c) Provide the client information about the study and seek her informed consent to participate in the study.

E.2 Medical eligibility and contra-indications

We use the U.S. Centre for Disease Control and Prevention's recommendations for "U.S. Medical Eligibility Criteria for Contraceptive Use, 2016" to determine methods that are contraindicated for various conditions the clients may have. The main considerations are the following:

- Recent delivery of a baby
- Breastfeeding
- Unexplained vaginal bleeding
- Current blood pressure/history of hypertension
- Risk factors such as older age (>35), smoking, diabetes
- Medications such as TB drugs, Barbiturates, and Antiretroviral drugs

A large number of medical eligibility rules relating to the conditions above are programmed into the algorithm and when a condition is satisfied, the method is ruled out and excluded from rankings. When this happens, the job-support tool displays a message at the top of the method choice section that certain methods are being excluded due to medical eligibility criteria, so that the provider can explain the client why she is not being given the option to discuss that method.

E.3 Method rankings

The tablet-based job-support tool takes client preferences regarding how long to wait before becoming pregnant and the importance of various side effects into account, in order to produce method rankings. The algorithm uses three key criteria:

1. How long she would like to wait before becoming pregnant, and
2. How strongly she feels about avoiding the following three categories of side effects:
   (a) Increased bleeding and cramping,
   (b) Decreased bleeding, spotting, and amenorrhea, and
   (c) Weight gain
3. Typical use effectiveness of each method

Based on these criteria the algorithm creates a score for each method. The algorithm uses evidence on the average side effects of each method from the existing peer-reviewed literature. Similarly, the typical use effectiveness data used by the algorithm comes from peer-reviewed literature.

For example, if the client feels strongly about minimizing the chances of all three categories of side effects and would like to wait more than one year before getting pregnant, the ranking of methods (from most suitable to least suitable) is as follows: IUD, pill, (lactational amenorrhea method or LAM), implant, and the injectable.[21] Note that in this example, the pill, which is a short-acting method with a typical use effectiveness much lower than the implant and the injectable, is ranked above both methods because of the client's preferences regarding side effects.

[21] The LAM method is included in the rankings if a client has (i) given birth in the past six months; (ii) is fully breastfeeding; and (iii) has not menstruated since birth; and excluded otherwise.

In contrast, consider a client who wishes to have no more children and does not care about any of the side effects. The method rankings for such an individual is: IUD, implant, injectable=(LAM), and the pill. The reader will now notice that because the client is interested in avoiding pregnancies altogether and is not concerned with side effects, long-acting methods are ranked higher, while the pill, which has the mildest expected side effects, is ranked at the bottom. The algorithm sometimes produces identical scores for two or more methods that result in a tie in the rankings. In such cases, the client is told that two (or more) methods are equally suitable for her and the tablet uses an internal random number generator to decide the ordering of the tied methods for discussion.

E.4 Consultation cue cards

This section shows the two sides of the consultation cue cards for the implant:

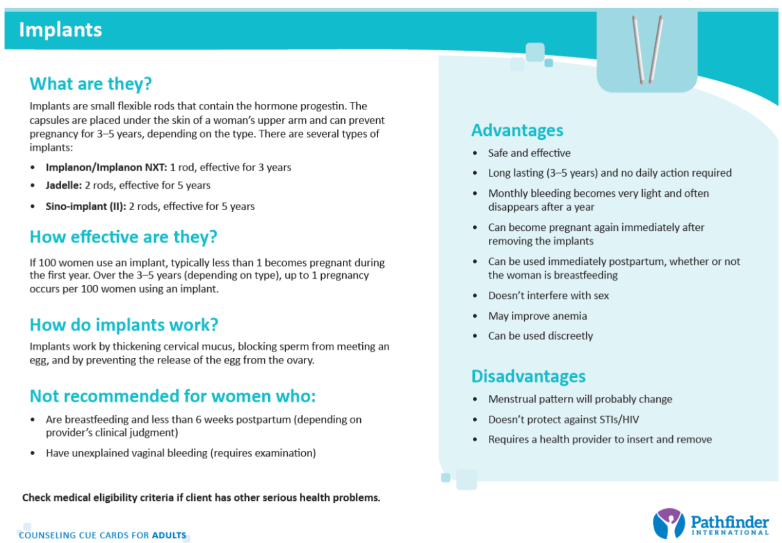

Figure E1: Example cue card used during the consultation, Implant (Front of the card)

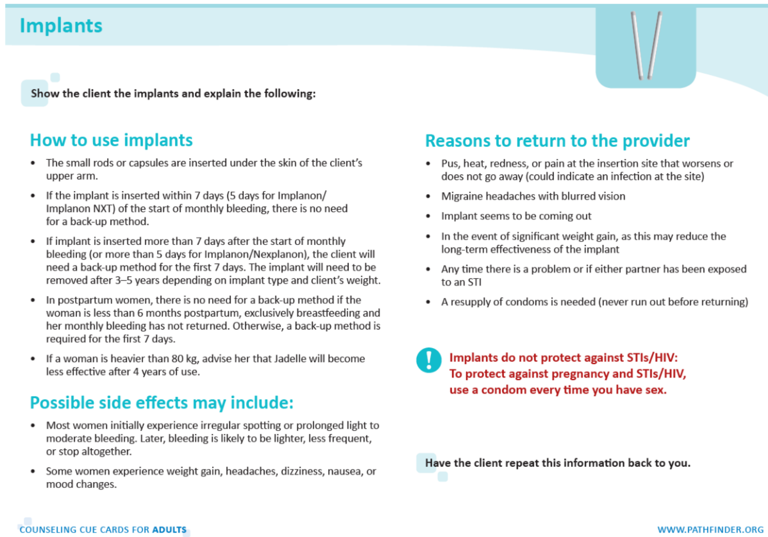

Figure E2: Example cue card used during the consultation, Implant (Back of the card)

F CATE estimation details

In this section, we explain in detail how the quantities in Section 4.3 were computed. We use the following notation: Y_i is the binary indicator that client i adopted a LARC; X_i is a vector of covariates that includes the randomly assigned counseling method (a categorical variable with values MiM, IDM or SDM); W_i is a binary variable representing whether the client faced full prices (0) or was given any discounts (1). Using potential outcome notation, $(Y_i(1), Y_i(0))$ represents the LARC adoption outcome of client i under treatment and control. Our preliminary object of interest is the conditional average treatment effect function $\tau(x) := \mathbb{E}[Y_i(1) - Y_i(0)|X_i = x]$.

In Section 4.3, the CATE function was fitted using the `causal_forest` function from the `R` package `grf`. To rank observations, we proceeded as follows. First, we divided observation into subset depending on counseling assignment. Then, we fit a separate causal forest for each subset. Before fitting the forest, each observation received a randomly chosen label $\ell_i \in \{1, ..., 10\}$. When fitting and predicting the forest, we ensured that CATE estimates for observations with label ℓ were computed using trees that did not use any observations with that same label during fitting.[22] Within each subgroup with the same label, observations were ranked into *strongly*- or *weakly*-affected if their predicted CATE was above or below the median CATE prediction within that label. Ranking only observations within a label ensures that the relative rank between two observations does not use data from either observation. Finally, we concatenated all the predictions and rankings. Having labeled observations as above, to construct Table 3 we averaged covariate values by rank.

[22]This is accomplished by passing the label vector to the `clusters` argument in `causal_forest`.

To obtain the results in the first row of Panel A in Table 2, we estimated the ATE within each subgroup by comparing the average LARC adoptions between observations treated with different treatments. A more efficient estimate, shown in the second row of Panel A in Table 2, was be obtained by compared averages of augmented inverse propensity (AIPW) scores,

$$\widehat{\Gamma}_i := \hat{\tau}(X_i) + \frac{W_i}{e(X_i)} \left(Y_i - \hat{\mu}(X_i, 1)\right) - \frac{1 - W_i}{1 - e(X_i)} \left(Y_i - \hat{\mu}(X_i, 0)\right), \tag{2}$$

where $\hat{\mu}(X_i, w)$ is an estimate of the conditional expectation $\mathbb{E}[Y_i(w)|X_i]$ (obtained as a by-product when fitting the forest), and $e(X_i, w)$ are known treatment assignment probabilities. Estimates based on (2) are unbiased, consistent, asymptotically normal, and in large sample typically have lower variance than their counterparts based on sample averages.